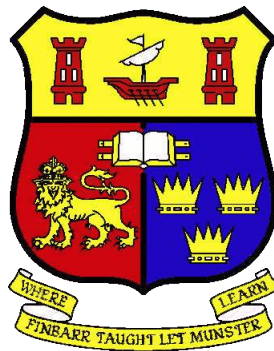


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Techno-Economic and Socio-Economic Modelling of Energy in Road Transport to Inform Climate Policy

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Declaration

“This is to certify that the work I, Eamonn Mulholland, am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism.”

Eamonn Mulholland

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Executive Summary

The release of increasing amounts of anthropogenic greenhouse gas emissions and the corresponding global temperature rise has prompted a growing political consensus on a decarbonised future to prevent any sustained economic or environmental harm. Many countries are using modelling tools to develop strategies and policy measures to deliver timely and effective reductions of harmful greenhouse gas emissions across all energy related sectors. Techno-economic models have a track record in developing low carbon pathways from a technical standpoint, though they have generally failed to adequately account for the underlying socio-economic behaviour which drives consumers in their choices. This thesis highlights and addresses this failing in two parts with a focus on road transport, one of the most difficult sectors to decarbonise.

The first part of this thesis reviews the functionality of techno-economic road transportation models and identifies the limitations associated with their operation. The thesis expands upon the International Energy Agency's global techno-economic simulation transport model, MoMo, with a focus on the freight sector. Next, a national focus is provided, building and applying a simulation techno-economic model of Ireland's light commercial vehicle stock. This is soft-linked with an optimisation model of the Irish energy system, Irish TIMES. This multi-model methodology is then applied to Ireland's private car sector, where the limitations of using techno-economic modelling techniques in isolation are identified.

The second part of this thesis develops novel socio-economic approaches and integrates these with techno-economic models. A review of socio-economic modelling methods within transport models is performed, identifying the options available for integration with other models. These methods are then tested on the Irish and Danish private car sector, where a consumer choice model is built and integrated with a techno-economic simulation model. Finally, this integration is further coupled with a TIMES optimisation model, focusing on Denmark, which uses a time travel budget to further include behavioural realism into transport focused modelling.

The contribution of this thesis is the improvements made to the modelling methods and more robust evidence base for developing sound low-carbon policy measures by integrating techno-economic and socio-economic frameworks coupled with a combination of optimisation and simulation modelling methods within the road transportation sector.

Units and Abbreviations

AD	Anaerobic Digestion
AFV	Alternative Fuelled Vehicles
AMT	Annual Motor Tax
B2DS	Beyond Two Degree Scenario
BaU	Business as Usual
BECCS	Bio-energy Carbon Capture and Storage
BEV	Battery Electric Vehicle
Bio-DME	Bio-Dimethyl Ether
BOS	Biofuel Obligation Scheme
BtL	Biomass-To-Liquid
BU	Bottom-Up
CES	Constant Elasticities of Substitution
CGE	Computable General Equilibrium
CH ₄	Methane
CNG	Compressed Natural Gas
CO ₂	Carbon Dioxide
CO ₂ eq	Carbon Dioxide Equivalent
COP21	21st Meeting of The Conference of Parties
CSO	Central Statistics Office
CVRT	Commercial Vehicle Road Worthiness Test
E3	Energy-Economy-Environment
EJ	Exajoules
ERS	Electric Road Systems
ESRI	Economic and Social Research Institute
ETP	Energy Technology Perspectives
EU	European Union
FI	Full Integration
GDP	Gross Domestic Product
GFEI	Global Fuel Economy Initiative
GHG	Greenhouse Gas
GNI	Gas Networks Ireland

GNP	Gross National Product
GVW	Gross Vehicle Weight
ha	Hectares
HDV	Heavy Duty Vehicle
HERMES	Harmonised Econometric Research For Modelling Economic Systems Model
HFT	Heavy Freight Truck
HVO	Hydrotreated Vegetable Oil
IAM	Integrated Assessment Model
ICE	Internal Combustion Engines
IEA	International Energy Agency
IMC	Independent Model Convergence
INDC	Intended Nationally Determined Contribution
IPCC	The Inter-Governmental Panel on Climate Change
kg	Kilograms
ktoe	Kilo tonnes of Oil Equivalent
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCV	Light Commercial Vehicle
LNG	Liquified Natural Gas
LRR	Low Rolling Resistance
ltr	Litres
MaaS	Mobility as a Service
MFT	Medium Freight Truck
MJ	Mega Joules
MNL	Multinomial Logit Model
MoMo	Mobility Model
MTS	Modern Truck Scenario
NCT	National Car Test
NDC	Nationally Determined Contributions
Nm	Newton Metre
Non-ETS	Non-Emissions Trading Scheme
NO _x	Nitrogen Oxides
NRA	National Road Authority
NREAP	National Renewable Energy Action Plan

OECD	Organisation for Economic Co-Operation and Development
OEM	Original Equipment Manufacturer
PET	Pan European Times
PHEV	Plug-In Hybrid Electric Vehicle
PI	Partial Integration
PJ	Peta Joules
PPP	Purchasing Power Parity
RED	Renewable Energy Directive
RES	Reference Energy System
RES-T	Renewable Energy in Transport
RP	Revealed Preference
RQ	Research Question
RTS	Reference Technology Scenario
SEAI	Sustainable Energy Authority of Ireland
SEC	Specific Energy Consumption
SO _x	Sulfur Oxides
SPS	Stated Preference Survey
t	Tonnes
TD	Top-Down
TIMES	The Integrated Market Allocation Energy Flow Optimisation Model System
tkm	Tonne-Kilometres
TPS	Tyre Pressure Systems
TTB	Travel Time Budget
TTI	Travel Time Investment
TTW	Tank-To-Wheel
UN	United Nations
VS	Volatile Solids
VAT	Value Added Tax
vkm	Vehicle Kilometres
VRU	Vehicle Registration Unit
W	Watts
WEO	World Energy Outlook
WTT	Well-To-Tank
WTW	Well-To-Wheel
wwt	Wet Weight Tonnage

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Chapter 1

Introduction

1.1 Background

Atmospheric concentrations of anthropogenic greenhouse gases (GHG) have reached levels unprecedented for at least the previous 800,000 years. It is extremely likely that this rise in GHG emissions has been the dominant cause of the observed warming since the middle of the twentieth century (IPCC, 2014a). Since entering into force in 1994, the United Nations Framework Convention on Climate Change (UNFCCC) has been attempting to find a global solution to the challenges posed by climate change associated with the observed warming. In an attempt to combat increased warming, the 21st meeting of the Conference of Parties in Paris (COP21) concluded with an agreement to hold the increase in warming to “well below 2°C above pre-industrial levels”, and to pursue efforts to “limit temperature increase to 1.5°C” above pre-industrial levels (UNFCCC, 2016). However, this agreement has already proved challenging. Limiting global temperature rise to 1.5°C above pre-industrial levels at a probability of greater than 66% relates to a global carbon budget of 400 GtCO₂ as of 2011 (IPCC, 2014a). Emphasising the challenge is the fact that global emissions from fuel combustion in 2014 alone amounted to 32.4 GtCO₂ (IEA, 2016a), which would exceed the 1.5°C budget in 12 years. To add to this challenge, the year 2015 ranked as the warmest on record at the time, and globally averaged temperature measurements indicate a warming of 0.97°C up to this same year, relative to an averaged 1860 – 1880 baseline (Otto et al., 2015).

The energy sector has contributed singularly to this temperature rise, accounting for approximately two thirds of global GHG emissions (IEA, 2016b). Transportation stands as one of the highest consuming energy-related sectors, representing 28% of global energy consumption in 2014 (IEA, 2016c). The task of reducing global transportation GHG emissions is challenging, yet imperative, in stabilising global temperature rise, and will require both short-term and long-term mitigation strategies to succeed (IPCC, 2014b). The dependence of this sector on liquid fossil fuels has created substantial carbon lock-in making it difficult for a switch over to renewable alternatives – in 2014 the penetration of renewables in transportation had the lowest share of any other sector (see Figure 1.1).

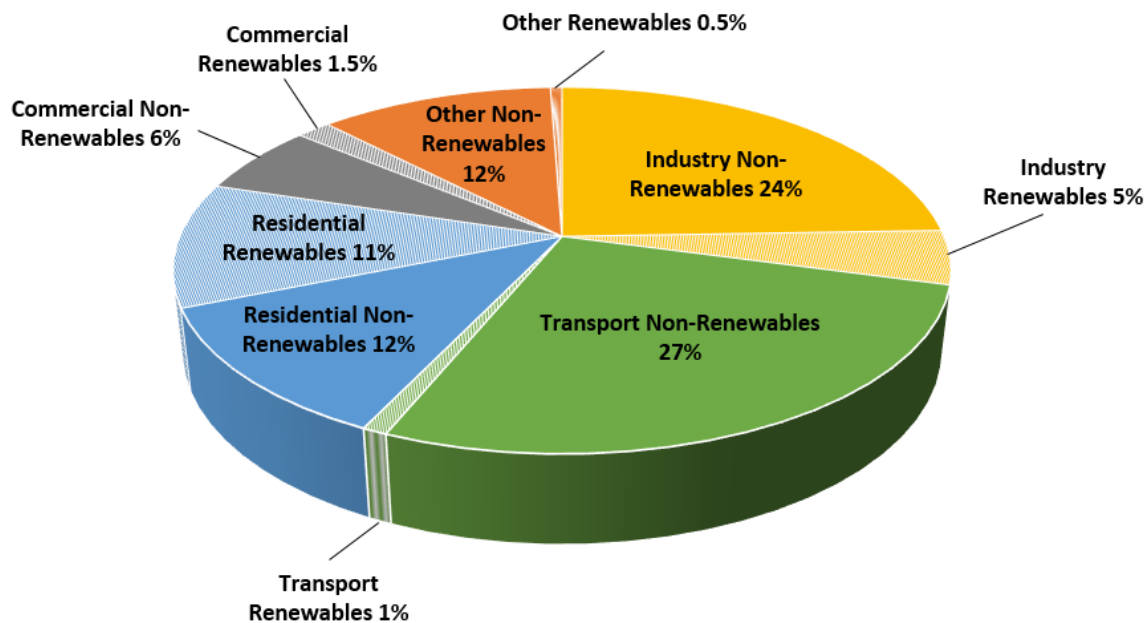


Figure 1.1: Global renewable¹ and non-renewable shares from energy related sectors in 2014. Source: (IEA, 2016c)

This carbon lock-in arises despite the ostensible availability of a plethora of low carbon technology alternatives. Electric vehicles (EVs), for example, have undergone significant development in the past decades with falling costs of Lithium-ion battery packs, which are expected to continue to fall (Nykqvist and Nilsson, 2015). Despite this, the uptake of EVs has been subject to numerous consumer barriers (McCollum et al., 2016), preventing the penetration of electric transport reaching ambitions set by certain governments. The Irish Government, for example, set a target to roll-out 50,000 EVs by 2020, while the stock as of 2015 amounted to slightly less than 600 vehicles (DTTAS, 2017). The challenge lies not just in the availability of technical solutions, but also with the underlying behaviour of individuals and their willingness (or lack thereof) to switch to renewable alternatives. Mitigation strategies must consider both aspects to be considered effective.

The International Energy Agency (IEA) proposes a combination of both technological and behavioural measures to address transport CO₂ reduction: avoid, shift and improve. Transportation policies may be categorised in a similar manner. For example, the Irish Government released a transport policy plan entitled 'Smarter Travel' aimed at reducing overall transport activity (avoid) (DTTAS, 2009). The State of California instigated a Zero Emission Vehicle program in 2009 as a means of incentivising a switch to alternative methods of transportation (shift) (CARB, 2009). The European Union (EU) implemented an emissions standard mandate for the manufacturers of automobiles in 2009, limiting

¹ Renewables in this context include hydroelectricity, geothermal, solar photovoltaic, solar thermal, tide, wave, ocean, wind, solid biofuels, biogases, liquid biofuels and renewable municipal waste

the amount of specific emissions of each new vehicle by a target year (improve) (European Parliament, 2009a). While a holistic approach combining many strategies has the potential to be more effective, the actual combined effect of any portfolio of policies is subject to significant uncertainty about the future. To address and minimize this uncertainty, energy system models have become widely used for the effective design, planning, implementation and assessment of multiple policies for the transport sector.

There are currently a myriad of such transportation models with a variety of purposes and timelines focused at a global level e.g., (Kyle and Kim, 2011, Waisman et al., 2013, Yeh et al., 2017), regional level e.g., (Seixas et al., 2015), and at a national level e.g., (Zhang et al., 2016). The prevalence of these transport-orientated models with both a wide and narrow geographic scope is certainly important for the act of informing policy, and understanding the potential effectiveness at a national and international level. Such is the potential importance and usefulness of these models that they have become increasingly scrutinized by users and non-users alike. For example, the accuracy of these models depends on the technical and behavioural representation within. In addition, and more critically, the framework and type of model can reflect a particular worldview with its own shortcomings or biases, which may or may not be appropriate for understanding all transport problems.

Traditionally, techno-economic modelling frameworks have been dominant in considering low carbon pathways for the transport sector. While this modelling approach is necessary to understand the viability of specific technologies in long-term decarbonisation, a stand-alone techno-economic model stands susceptible of overlooking the barriers faced by transport agents in purchasing alternative fuelled vehicles, such as EVs or natural gas trucks. Moving away from neo-classical economic methods of modelling, whereby transport agents are represented as rational decision makers, towards an integrated techno-economic and socio-economic approach allows for a more accurate representation of behavioural realism. Without accounting for consumer behaviour, policy makers are liable to creating ineffective policies, and thus models which aim to support stringent decarbonisation policies must have both a strong techno-economic and socio-economic foundation. This thesis addresses this necessity through exploring both model frameworks by assessing, building upon, and creating new techno-economic and socio-economic models with the intention of informing climate policy measures capable of supporting a deep decarbonisation of the transportation sector.

1.2 Purpose of Thesis

The aim of this thesis is to improve the robustness of models that inform policy decisions for the road transport sector. To achieve this aim, this thesis uses a combination of techno-economic and socio-economic sectoral simulation and optimisation transport models to provide valuable policy insights into methods of moving the transport sector towards a low-carbon future at both a national and international level. The main focus of this thesis is given to passenger vehicles and road freight vehicles which, when combined, constituted 75% of global transport GHG emissions in 2015 (IEA, 2016d), while available options for other forms of road transport are explored in the latter section of this research. This thesis utilises a variety of existing modelling methodologies and applies newly developed and unique techniques to analyse the transport. These modelling techniques identify a combination of technology pathways and policy roadmaps with the potential of breaking the barriers opposing a penetration of low carbon road vehicles from both a technical and social viewpoint. The focus of this research is therefore threefold. Firstly, to use and build upon current techno-economic methodologies for modelling the transport sector and to understand the limits of these methods. Secondly, to review socio-economic modelling methods and integrate them into traditional techno-economic models. Thirdly, to develop robust knowledge-based policies capable of informing policy makers of the effectiveness and cost (both monetary, and social) of certain policy packages within the transport sector using the former two focus points. Following these focus points, this thesis sets out to answer the following research questions (RQs):

- RQ 1.** *What policies can assist in a decarbonisation of road freight vehicles?*
- RQ 2.** *What policies can assist in a decarbonisation of passenger vehicles?*
- RQ 3.** *What transportation policies may adhere to a <2°C scenario?*
- RQ 4.** *What is the current state-of-the-art in techno-economic transportation models?*
- RQ 5.** *What are the limitations and potential improvements of techno-economic models?*
- RQ 6.** *What is the current state-of-the-art in socio-economic modelling methods, and how can these be integrated with techno-economic modelling methods?*

The following section summarises the outline of this thesis, and how the various chapters of this thesis correspond to these research questions.

1.3 Outline of Thesis

- **Part I – Techno-Economic Modelling:** A range of sectoral simulation and optimisation techno-economic models are built upon or created to develop baseline projections and low-carbon scenarios for the road freight and private transport sector.
 - **Chapter 2 – Global Freight (RQs 1 and 3):** A road freight demand module is built and integrated into the IEA’s Mobility Model (MoMo) – a techno-economic model. This module is built through exploring the historic trends in activity within the global road freight sector, and projecting these trends to 2050 using data generated by the Organisation for Economic Co-operation and Development (OECD). The activity projections are used to generate an energy demand baseline of global road freight and identify the policies necessary for a substantial reduction in CO₂ emissions through efficiency improvements, logistic and operation improvements, and low carbon fuels and fuel technologies.
 - **Chapter 3 – National Freight (RQs 1 and 3):** This chapter follows on from the previous by considering the low carbon opportunities for a specific national case of the road freight sector in Ireland under a different modelling framework. Technology-rich data is used to generate a stock simulation model of light goods vehicles which is then linked with a techno-economic optimisation model – Irish TIMES – to provide cost optimal low carbon pathways via effective national policy.
 - **Chapter 4 – National Private Cars (RQs 2, 3, and 4):** A similar methodology to that of Chapter 3 is used, whereby a sectoral simulation model of the Irish private car sector is soft-linked with Irish TIMES to generate technology pathways, policy roadmaps, and specific enabling measures for the private transport sector. This chapter concludes by highlighting the limitation of only using techno-economic models, and identifies the need to establish a socio-economic framework to generate more realistic scenarios and policies.
- **Part II – Socio-Economic Modelling:** Upon determining the limitations of stand-alone techno-economic models, an introduction of socio-economic modelling techniques is integrated into techno-economic models to present a more holistic framework.
 - **Chapter 5 – Review of Behaviour Representation in Transport Modelling (RQ 5):** An extensive literature review is carried out on the current methods of modelling behaviour within the transport sector – specifically focusing on methods of linking model types, modelling consumer choice and modelling modal choice under various frameworks.

- **Chapter 6 – Representing Consumer Choice for Private Vehicles (RQs 2 and 5):**
Drawing from the review carried out in Chapter 5, socio-economic techniques are adapted and improved using empirical data for Ireland and Denmark to model the limitations faced by private vehicle consumers when purchasing a range of vehicle technologies, giving a special focus to the emissions and cost of various national policies.
- **Chapter 7 – Integrating Techno-Economic and Socio-Economic Modelling to analyse a well-below 2°C Scenario (RQ 6):** The techno-economic and socio-economic methods developed throughout the thesis are combined in the final chapter to create a technology and behaviour rich model of the Danish energy system, with the intention of understanding what policies are required at a national level to comply with a well-below 2°C scenario.

The structure and flow of this thesis can be summed up by Figure 1.2:

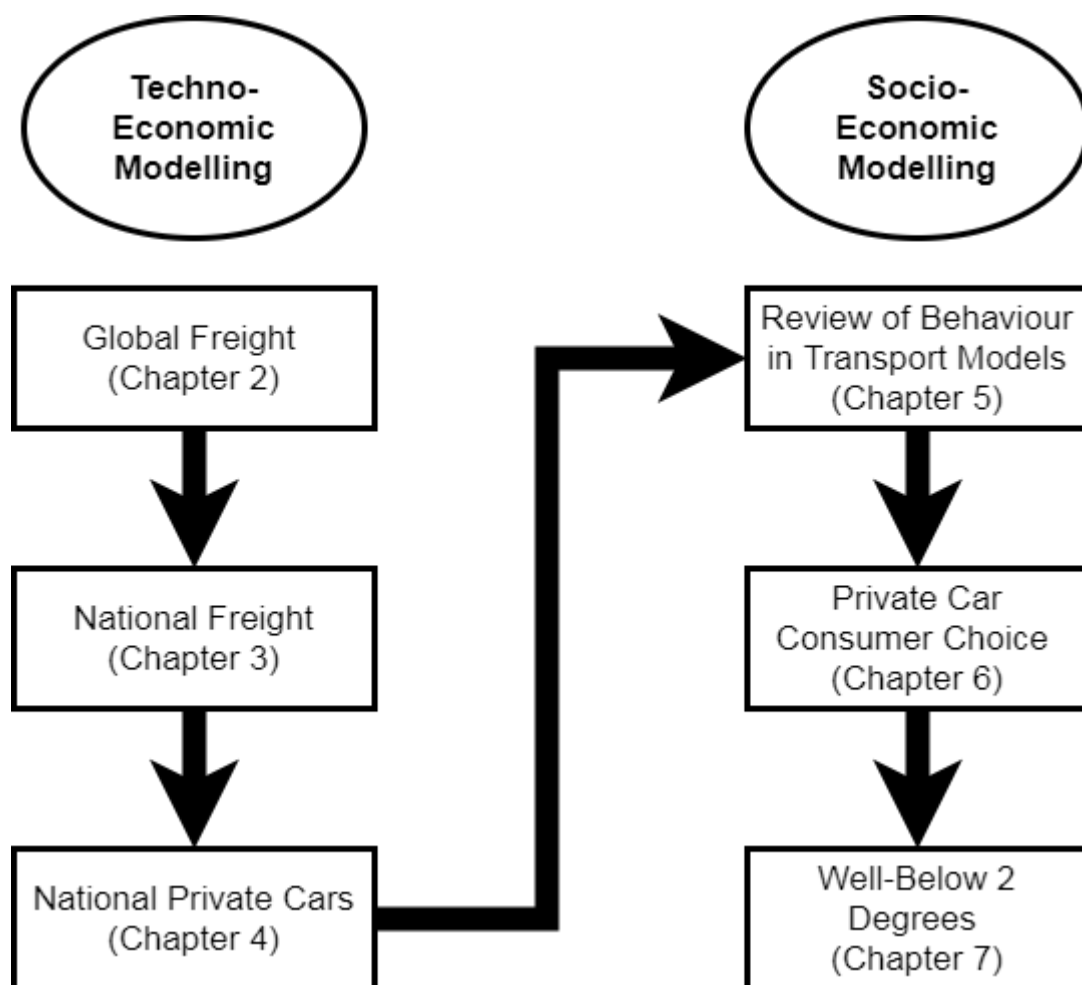


Figure 1.2: Thesis flow chart

1.4. Methodology

This thesis employs a combination of modelling techniques (techno-economic/socio-economic) within different modelling frameworks (top-down/bottom-up, simulation/optimisation), with a variety of geographical scopes throughout (international/national). The nature of these modelling approaches allows them to be used for a variety of purposes, with numerous advantages and disadvantages associated with each type. Table 1.1 provides a description of the modelling methods and frameworks explored in this thesis, and an overview of the variety of these approaches and the methodology adopted within this thesis is explained further throughout this section.

Table 1.1: Summary of modelling methods and frameworks explored in this thesis

Modelling Method	Description	Modelling Framework	Description
Optimisation	Optimisation models find least cost energy systems pathways, subject to certain constraints, including policy targets	Techno-Economic	Techno-economic models use a dataset characterised by technical and monetary detail, usually assuming consumers are economically rational agents with a perfect knowledge of the market
Simulation	Simulation models generate 'what if' scenarios to conceptualise the effect of certain changing variables (including policy measures) on energy demand and supply	Socio-Economic	Socio-economic models account for behavioural realism within the modelled system by accounting for consumer preferences which may affect decision making

1.4.1 Modelling Techniques and Frameworks

Techno-economic and socio-economic models can be loosely categorised as either simulation models or optimisation models, which represent alternate ways of considering the energy system. Simulation models, for example, tend to use a bottom-up approach whereby a range of technical and policy measures may be simulated throughout to generate the specific impact of such measures. While this technique may be considered to give a more realistic representation of the system being modelled, it might not give an optimal solution to a certain measure. Optimisation models, on the contrary, may be used to generate least-cost pathways given a certain constraint on the system under analysis, e.g., identifying the least cost method of limiting CO₂ emissions to comply with a 1.5°C temperature rise. Here the model selects from a range of technology options available with the potential of adhering to the system constraints imposed while minimising the net present value from an energy planner's perspective. While this method provides a least-cost result, traditional optimisation models have failed to represent a high level of societal behaviour, leading to irregularities such as very sudden shifts in the system towards new technologies capable of meeting the system constraints, also known as the 'winner takes all' phenomenon.

An integration of both simulation and optimisation techniques has the potential to combat the weaknesses of both models, and thus features heavily throughout this thesis. However, adopting this multi-modelling approach may still provide unrealistic results without the inclusion of socio-economic methods. This thesis therefore reviews the current methods of adopting behaviour into a transport modelling framework, with an emphasis on consumer choice related to the private vehicle market. This review feeds into the provision of a realistic behaviour representation of the transportation system capable of identifying the implications and effectiveness of policy measures centred on decarbonisation pathways.

The primary output of this thesis consists of a set of suggestions for model-based policy measures capable of decarbonising different areas of the transport sector. However, these measures are intended to be insights, not answers, to how one might begin to decarbonise the transportation sector. Therefore, the modelling presented within this thesis creates an evidence base which is more valuable at the early stages of policy-making, i.e., initiating discussions on energy policy, rather than at the later stages of the actual formation of energy policy.

1.4.2 Geographical Scope

The level of geographical granularity examined plays a significant role throughout this thesis. The agreement made at COP21 was largely a global commitment. This calls for the use of models with a global geographic scope to understand the magnitude of the effort required to adhere to this commitment. While advantageous in carrying a potentially holistic view of the entire energy system, this level of scope falls subject to a lower quality of data in certain regions, especially developing countries, and may misalign the level of effort of which certain regions are capable. Chapter 2, for example, presents a global assessment of the road freight industry and outlines the potential of efficiency improvements, fuel switching, and logistic improvements under a simulation modelling framework, while Chapter 3 then considers the road freight sector for a specific case, Ireland, under a combination of optimisation and simulation modelling. While the outcomes of Chapter 2 show what may be considered a realistic pathway at a global scale, Chapter 3 further explores the same sector under a soft-linked modelling framework to show what may be considered both cost-optimal and technically achievable. It is therefore necessary to consider both global and national level transportation based modelling, and thus global assessments are carried out alongside case studies of both Denmark and Ireland, due to their ambitious long-term GHG reduction targets planned within the transport system.

1.5 Role of Collaborations

This thesis is the summation of my research work in this area; however, it would not have been possible without a range of collaborative research which played a significant part in the formation of all chapters. These collaborations were carried out within some of the leading institutions of transportation energy modelling to ensure originality of content and to add to existing state-of-the-art modelling techniques. This section aims to provide clarity to the role of these collaborations. It should further be noted that these chapters are based on a combination of journal papers (two published, three in review), one report (published) and one book chapter (under review).

- **Chapter 2** was carried out in collaboration with the transport division in the Sustainability, Technology and Outlooks department within the International Energy Agency, specifically with Jacob Teter and Pierpaolo Cazzola. While I wrote this chapter in its entirety and carried out all work relating to the historic trends of road freight activity, the IEA carried out the scenario development using the Mobility Model. This work was published by the IEA in the form of a report entitled “The Future of Trucks – Implications for Energy and the Environment” and has been submitted as a journal paper of which I am lead author. Prof. Brian Ó Gallachóir and Dr. Fionn Rogan provided guidance and reviewed drafts.
- **Chapter 3** has been published in a peer reviewed journal of which I am lead author. I built and ran all scenarios for the light goods vehicle stock model, while Richie O’ Shea from the Biofuels and Bioenergy Research Group carried out the resource assessment of biofuels, and Rodger O’ Connor from Gas Networks Ireland provided real-world data on the performance of compressed natural gas vans. Prof. Brian Ó Gallachóir and Dr. Fionn Rogan provided guidance and reviewed drafts.
- **Chapter 4** has been published in a peer reviewed journal of which I am lead author. In this work, I updated the previously built CarSTOCK model, built a market share algorithm, and ran all scenarios, with assistance from Alessandro Chiodi of the Energy Policy and Modelling Group in generating the results from the Irish TIMES model. Prof. Brian Ó Gallachóir and Dr. Fionn Rogan provided guidance and reviewed drafts.
- **Chapter 5** is the result of a paper submitted to a peer-reviewed journal and was carried out in collaboration with the management engineering department in the Danish Technical University. Here I carried out the review of the methods of model linkage, review related to modelling methods, and contributions towards the consumer choice methodology. Giada Venturini and Jacobo Tattini (the joint first authors) created the taxonomy of modelling methods, carried out the review on modal shift modelling methods and also contributed to

the review on modelling consumer choice. Prof. Brian Ó Gallachóir and Dr. Fionn Rogan provided guidance and reviewed drafts.

- **Chapter 6** is the result of a paper submitted to a peer-reviewed journal of which I am first author. This was carried out in collaboration with Christopher Yang and Kalai Ramea from the Institute of Transportation Studies in UC Davis, and Jacopo Tattini from the management engineering department in the Danish Technical University. I carried out all modelling, scenario development, and writing of this work. Jacopo Tattini provided the information for the Danish private vehicle market with constant guidance from Christopher Yang and Kalai Ramea throughout. Prof. Brian Ó Gallachóir and Dr. Fionn Rogan also provided guidance and reviewed drafts.
- **Chapter 7** is the result of a book chapter submitted to the ETSAP published book by Springer “Well Below 2 Degrees”. For this work, I featured as second author and created the consumer choice model and the car stock model for the Danish private transport sector, along with running all scenarios using these models. I wrote the introduction section of this chapter, alongside everything related to the consumer choice model. I also calculated the national carbon budgets for Denmark used in this Chapter. Jacopo Tattini led the work using the Danish TIMES model, and both Mohammad Ahanchian and Giada Venturini assisted with the framing of policies acting as inputs for the models. Prof. Brian Ó Gallachóir and Dr. Fionn Rogan provided guidance and reviewed drafts.

1.6 Thesis Outputs

1.6.1 Journal Papers

Mulholland, E., Teter, J., Cazzola, P., Ó Gallachoir, B. P., “The long haul towards decarbonising road freight – a global assessment to 2050”, *Energy Policy*, submitted in October 2017

Mulholland, E., O Shea, R., Murphy, J. D., Ó Gallachoir, B. P., “Low carbon pathways for light goods vehicles in Ireland”, *Research in Transportation Economics*, vol. 57, pp. 53 – 62, 2016

Mulholland, E., Rogan, F., & Ó Gallachoir, B. P., “From technology pathways to policy roadmaps to enabling measures – a multi-model approach”, *Energy*, vol. 138, pp. 1030 - 1041, 2017

Venturini, G., Tattini, J., **Mulholland, E.**, & Ó Gallachoir, B. P., “Improvements in the representation of behaviour in integrated energy and transport models”, *International Journal of Sustainable Transport*, submitted in January 2017

Mulholland, E., Tattini, J., Ramea, K., Yang, C., Ó Gallachoir, B. P., “The cost of electrifying transport – evidence from an empirical consumer choice model of Ireland and Denmark”, *Transportation Research Part D: Transport and the Environment*, submitted in August 2017

Tattini, J., Ramea, K., Gargiulo, M., Yang, C., **Mulholland, E.**, Yeh, S., Karlsson, K., “Improving the representation of modal choice into TIMES energy system models – A case study for Denmark”, Applied Energy, submitted in August 2017

Haasz, T., Jochem, P., Gomez, J., Kunze, R., Deane, P., Fraboulet, D., Fahl, U., Keles, D., Coffineau, L., **Mulholland, E.**, Fichtner, W., “Perspectives on decarbonizing the transport sector in the EU28”, Energy Strategy Reviews, submitted in July 2017

Mulholland, E., Rogan, F., & Ó Gallachóir, B. P., “Techno-economic data for a multi-model approach to decarbonisation of the Irish private car sector”, Data in Brief, submitted in July 2017

1.6.2 Book Chapters

Tattini, J., **Mulholland, E.**, Venturini, G., Ahanchian, M., Gargiulo, M., Karlsson, K., “Long term strategy to decarbonise the Danish transportation sector”, Chapter in Springer Book “Towards a well below 2°C World: Moving to feasible zero-carbon roadmaps”, submitted in October 2017

1.6.3 Conference Proceedings

Mulholland, E., Teter, J., Cazzola, P., McDonald, Z., Ó Gallachoir, B. P., “The long haul towards decarbonising road freight – A global assessment to 2050”, 36th International Energy Workshop, University of Maryland, College Park, MD, USA, 12th – 14th July 2017

Mulholland, E., Tattini, J., Ramea, K., Yang, C., Ó Gallachoir, B. P., “The cost of electrifying transport”, Poster, STEPS Symposium, UC Davis, CA, USA, 23rd – 24th May 2017

Mulholland, E., Chiodi, A., Teter, J., Cazzola, P., Ó Gallachoir, B. P., “Development of a global freight transport demand tool”, Poster, Energy Systems Conference, QEI Centre, Westminster, London, UK, 14th – 15th June 2016

Mulholland, E., Teter, J., Cazzola, P., Ó Gallachoir, B. P., “Development of a global freight transport demand tool”, ITRN, DIT, Grangegorman, 2nd September 2016

Mulholland, E., O Shea, R., Murphy, J. D., Ó Gallachoir, B. P., “Low carbon pathways for light goods vehicles in Ireland”, ITRN, NUIG, Galway, 27th August 2015

Mulholland, E., Rogan, F., Gallachoir, B. P., “Top-down and bottom-up policy evaluation – A multi-model approach”, ECEEE Summer Study, Club Belambra Les Criques, Toulon, France, 2nd June 2015

1.6.4 Reports

Teter, J., Cazzola, P., Gul, T., **Mulholland, E.**, Le Feuvre, P., Bennet, S., Lagarde, Z., Kraayvanger, V., Rulz, P., “The Future of Trucks – Implications for Energy and the Environment”, IEA, July 2017

Kunze, R., Gomez, J., Keles, D., Haasz, T., Fahl, U., Dobbins, A., Fraboulet, D., Coffineau, L., Deane, P., **Mulholland, E.**, “Renewable Energy for Transport”, INSIGHT-E report prepared for the European Commission, September 2016

Pasquier, S., Thomas, S., Kreuzer, F., Teter, J., **Mulholland, E.**, “Transport, Energy Efficiency, & Behaviour Workshop”, IEA, Paris, May 2016

Mulholland E., Chiodi A, Deane J.P., Ó Gallachóir B.P., “Energy Scenarios for Ireland 2030 – 2050 focus on electricity in transport and heat sectors”, Report to EirGrid, November 2014

1.6.5 Invited Talks/Presentations

Mulholland, E., Ó Gallachóir, B.P., “The Long Haul towards the Decarbonisation of Freight”, International Council of Clean Transportation, 44 Montgomery Building, San Francisco, CA, USA, 20th June 2017

Mulholland, E., Ó Gallachóir, B.P., “The Past, Present and Future – An Analysis of Irish Transport Sector from 1900 to 2050”, STEPS Seminar, UC Davis, CA, USA, 22nd February 2017

Mulholland, E., Ó Gallachóir, B.P., “Stock Simulation Modelling in Transport”, DTU Transport Workshop, Copenhagen, Denmark, 26th January 2017

Mulholland, E., Rogan, F., Ó Gallachóir, B.P., “Low Carbon Options for Transport in Ireland”, Scientific Advisory Council, Beaufort Building, Ringaskiddy, Cork, 13th December 2016

Mulholland, E., Ó Gallachóir, B.P., “What will contribute more to emissions reduction in Ireland in 2020 – 50,000 EVs or improving the efficiency of petrol and diesel cars?”, ESRI-UCC Workshop, ESRI, Dublin, 9th June 2015

Mulholland, E., Ó Gallachóir, B.P., “The Effect of Vehicle Efficiency Improvements and Electric Vehicle Penetration on the Energy Sector in Ireland”, ENVIRON 25th Annual Consortium, Sligo IT, 8th – 10th April 2015

Mulholland E., Rogan F. and Ó Gallachóir B. “Soft-Linking a TIMES Model and Sectoral Simulation Model for Individual Policy Measures”, 66th Semi-annual IEA ETSAP Workshop, Copenhagen, Denmark, 17th – 18th November 2014

Part I - Techno-Economic Modelling

Chapter 2

The Long Haul towards Decarbonising Road Freight – A Global Assessment to 2050

Abstract

Road freight transportation is a key enabler of global economic activity while also a central consumer of fossil fuels, which presents a challenge in realizing a low-carbon future. To identify feasible decarbonisation solutions, this chapter first assesses significant drivers of activity in the road freight sector. It then uses these drivers to project road freight service demand, vehicle stock, mileage, sales, final energy demand, and well-to-wheel GHG emissions using the IEA's Mobility Model (MoMo) under two scenarios – the first incorporating the policy ambition of the Nationally Determined Contributions pledged at COP21, and the second extending ambitions to emission reductions that are in line with limiting global temperature rise to 1.75 degrees. In the former scenario, road freight well-to-wheel GHG emissions increase by 56% between 2015 and 2050, while in the latter, sectoral emissions are reduced by 60% over the same period, reflecting this thesis' assessment of the threshold of emission reductions potential of the road freight sector. This reduction is catalysed by policy efforts including fuel economy regulations, carbon taxes on transport fuels, differentiated distance-based pricing, widespread data-sharing and collaboration across the supply chain as enabled by digital technologies, and sustained investment in ultra-low and zero-carbon infrastructure and research development and deployment.¹

¹ Chapter based on contributions to the published IEA report "The Future of Trucks", and on a submitted journal paper: Mulholland, E., Teter, J., Cazzola, P., Ó Gallachoir, B. P., "The long haul towards decarbonising road freight – a global assessment to 2050", *Energy Policy*, Submitted in September 2017

2.1 Introduction

The road freight network acts as the arteries for global economic activity. As such, it is strongly linked to globalisation and economic development within nations – as a country’s economy develops, so does its level of infrastructure, freight logistics, and demand for goods, all of which tends towards an increase in freight demand. This trend has become most prominently apparent in developing countries in recent decades. For example, according to national statistics, road freight activity in India – measured in tonne-kilometres² (tkm) – increased by more than 9-fold over the period 1975 to 2015, (Ministry of Road Transport & Highways, 2009 – 2016) while road freight activity in China grew by more than 30-fold over this same period (The National Bureau of Statistics, 2015). Road freight activity in developed regions has not been as extreme, but is still significant: in the United States, for example, road freight tonne-kilometres increased by 2.5-fold (BTS, 2015) over the same forty year period (see Figure 2.1).

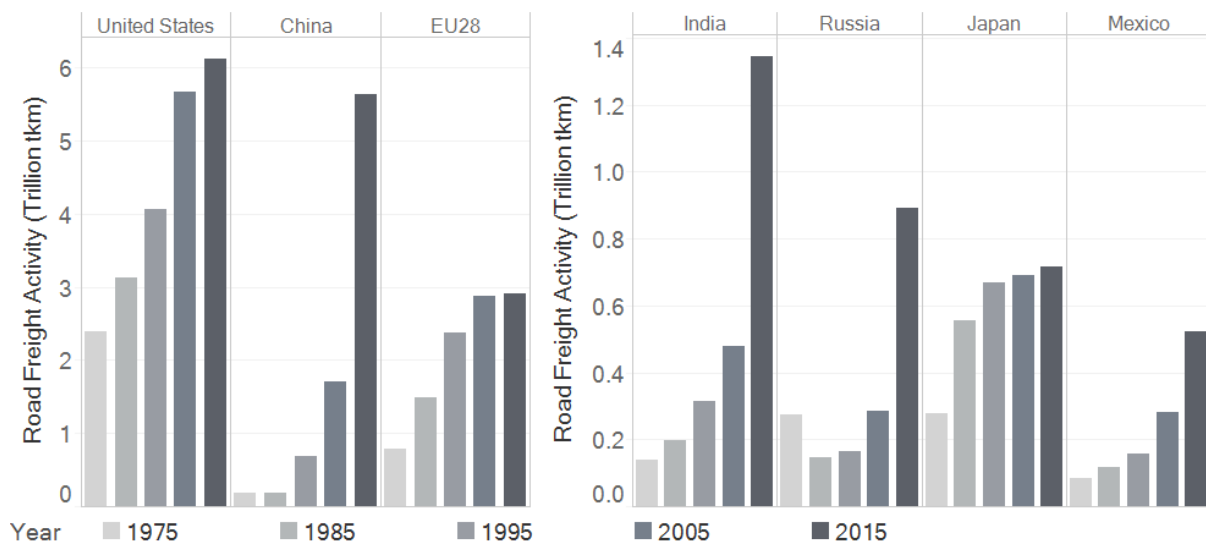


Figure 2.1: Road freight activity in major economies.³ Source: see Appendix A

The main driver of this recent growth, particularly in emerging countries, has been the robust economic development which has accelerated growth in on-road freight activity due to increased

² A common method of reporting freight activity is in tonne-kilometres, which is the product of the gross mass of the goods carried by the truck and the distance carried

³ Road freight activity shown in this graph is extrapolated based on national and regional data sources and calibrated using the IEA Mobility Model. The calibration is based primarily using data on vehicle sales, stocks, mileage, energy use per vkm and total energy demand, complemented by information on loads (including empty runs and laden trips with partial capacity utilisation). Vehicle mileages and load factors are the parameters with the greatest uncertainty in terms of data availability and reliability. This bottom-up approach, mainly focused on vehicles and energy, leads to estimations of total tkm that differ substantially from official statistics, especially in China, where official statistics report higher tkm values, and in the European Union, where Eurostat data provide lower tkm estimates

demand for consumer and industrial goods. Logistics, as well as intra- and inter-modal infrastructure tends to improve in tandem with economic development, thereby facilitating the more efficient movement of a greater volume of goods. In China, for example, the increase in freight activity over the past four decades is strongly driven by the globalisation of production activities, rapid industrialisation, and urbanisation coupled with the uneven geographic allocation of raw materials (Tian et al., 2014). However, this growth in road freight activity is not universal – in some developed nations aggregate road freight activity in tkm has slackened (in Japan) or even declined (in the UK). In the case of Japan, this can be related to a stagnating economy during the mid-90s following the economic collapse and to improvements in domestic logistics and operations (MLITT, 2015), while the reduction in road freight activity in the UK can be attributed to a structural shift in the economy as well as infrastructure improvements (Sorrell et al., 2012).

Despite the few cases of slackening growth or declining activity, which is a phenomenon limited to very rich countries over recent decades, overall global road freight activity is still largely on the rise. As a result, the road freight sector has played a growing role in global oil demand, accounting for 18% of global oil primary energy consumption in 2015, and about one-third of global transport final energy demand and well-to-wheel (WTW) global transport related greenhouse gas (GHG) emissions (IEA, 2017a). The sector's significant share in energy demand and GHG emissions, considered in light of the ambitious commitments of the world's major economies to decarbonisation, as laid out at the 21st meeting of the Conference of Parties (COP21), presents a challenge for road freight in transitioning from its current state, which is largely dominated by fossil fuels, towards low-carbon alternatives.

Despite the necessity of this transition if national commitments are to be achieved, there has been a lack of focus set on the road freight sector relative to others. For example, of the 133 submitted Intended Nationally Determined Contributions (INDCs), which represent national mitigation and adaption plans of 160 countries intended to comply with the ambitions set by COP21, only 13% mention freight while 61% mention passenger transport (Gota, 2016). In a further comparison against passenger cars, standards mandating minimum fuel economy of new sales of heavy-duty road freight vehicles in 2015 covered about 50% of heavy-duty truck sales, while fuel economy standards for light-duty vehicles covered more than 80% of sales, (ICCT, 2014, IEA, 2017b). Also considering that long-term growth of road freight transport activity and oil demand has been faster than that of passenger vehicles, and that this trend is expected to continue (IPCC, 2007, Eom et al.,

2012, Chapman, 2007), the lower level of focus given to road freight sector is likely to become increasing problematic as countries strive to adhere to their climate commitments.

A plethora of factors contribute to recent changes in road freight activity. While the link between economic development and road freight activity has been strongly evident in the past (Eom et al., 2012, IPCC, 2014b), there are many other factors, such as fuel prices, the distribution of natural resources, availability and quality of infrastructure, and population density, that influence shifting patterns of goods transport. The first aim of this study is to identify the key parameters, from a wide range of variables such as these, which are most consistently and highly correlated with road freight activity. Based upon comparison of various regressions, a log-log multivariate linear regression model is adopted to project future national trends in road freight activity. These are integrated into the International Energy Agency's (IEA) Mobility Model (MoMo) to provide the basis for activity demand-driven and policy-dependent scenarios of road freight vehicle fleet and sales, mileage, technology shares, energy demand, and GHG emissions. These projections are carried out under a Reference Technology Scenario (RTS), which considers all relevant policies and measures that are already adopted today or have been announced, including those of the INDCs pledged at COP21, and a Modern Truck Scenario (MTS), which focuses on the maximum policy commitments to (i) transition to more fuel-efficient road freight vehicles, (ii) improve logistics and operational efficiency (thereby reducing vehicle activity), and (iii) shift to ultra-low and zero-emission vehicle and fuel technologies. The resulting impact on energy demand and emissions in the MTS would be sufficient to bring the sector in line with ambitions stated in the COP 21 agreement to take efforts to limit global temperature rise to 1.75°C, with a probability of achievement of 50%.

This chapter is outlined as follows: first, the structure and functionality of the model used in this study, MoMo (Fulton et al., 2009, Yeh et al., 2017), are presented. Second, the key drivers of global freight activity and the methods for projecting future activity are discussed. Third, the options available for decoupling GHG emissions from the goods movement services delivered by the road freight sector are introduced, including vehicle efficiency measures, freight logistics improvements and a shift to alternative low-emission fuels and vehicles. The trends in activity identified are then used to project global long-term activity demand to 2050 in MoMo, with different degrees and rates of adoption of the three strategies described above used to back-cast developments in road freight consistent with the reference and low-carbon scenario. Finally, the chapter concludes with policy recommendations for public makers and other concluding remarks.

2.2 The Mobility Model (MoMo)

MoMo is a techno-economic simulation model designed to estimate and calibrate energy use and emissions from global motorised transport vehicle activity. It builds upon panel data extending from 1990-2015 (and in certain countries from 1970-2015) tracking vehicle sales and stocks and estimating on-road fuel economy, mileage, and vehicle occupancy/load factors. It accounts for the costs of vehicles, fuels, and related materials and resources, as well as infrastructure requirements. MoMo is based primarily on a descriptive approach, enabling the creation of “what-if” scenarios and back-casting to match transport-level sectoral and modal sub-sectoral GHG emission budgets. The main drivers for scenario developments are national population and GDP. Impacts of policies are modelled using elasticities (e.g. fuel price elasticity of demand) and case studies (e.g. on the impact of congestion charging, dynamic parking prices, etc.) for activity projections of both passenger and freight. The structure of the model allows it to be used, for example, to estimate the impact of fuel taxation on passenger and freight activity demand and then to assess how these change affects the portfolio of fuel demand and WTW GHG emissions

The calculation of energy consumption and GHG emissions performed in MoMo is based on the ASIF methodology developed by Schipper et al. (2000), adapting some of its aspects to fit with the available data for each region considered (see Equation 2.1).

$$G = \sum A_{i,j} * S_{i,j} * I_{i,j,k} * F_{i,j,k} \quad (2.1)$$

For road freight, GHG emissions (G) are calculated through the product of road freight activity in vkm (A), stock (S), energy intensity in MJ/vkm (I), and the GHG emissions intensity for the specific fuel in kg/MJ (F), where the emissions are calculated as the sum of well-to-tank (WTT) and tank-to-wheel (TTW) components. This product is summed for each truck fuel type (i), immatriculation year (j), and vehicle class (k). Load factors, which are based on calibration to national statistics, convert projections of tkm to vkm, and are modelled to develop according to relationships with national income (proxied by GDP per capita), and are responsive to assumed uptake of measures to improve road freight operational efficiency and logistics. Freight activity is calibrated to national reported freight statistics, and the resultant energy consumption is calibrated to the IEA energy balance, thereby providing a significant update to the method of accounting for activity within MoMo’s framework. A flow diagram of how MoMo calculates WTW emissions for the road freight sector is shown in Figure 2.2.

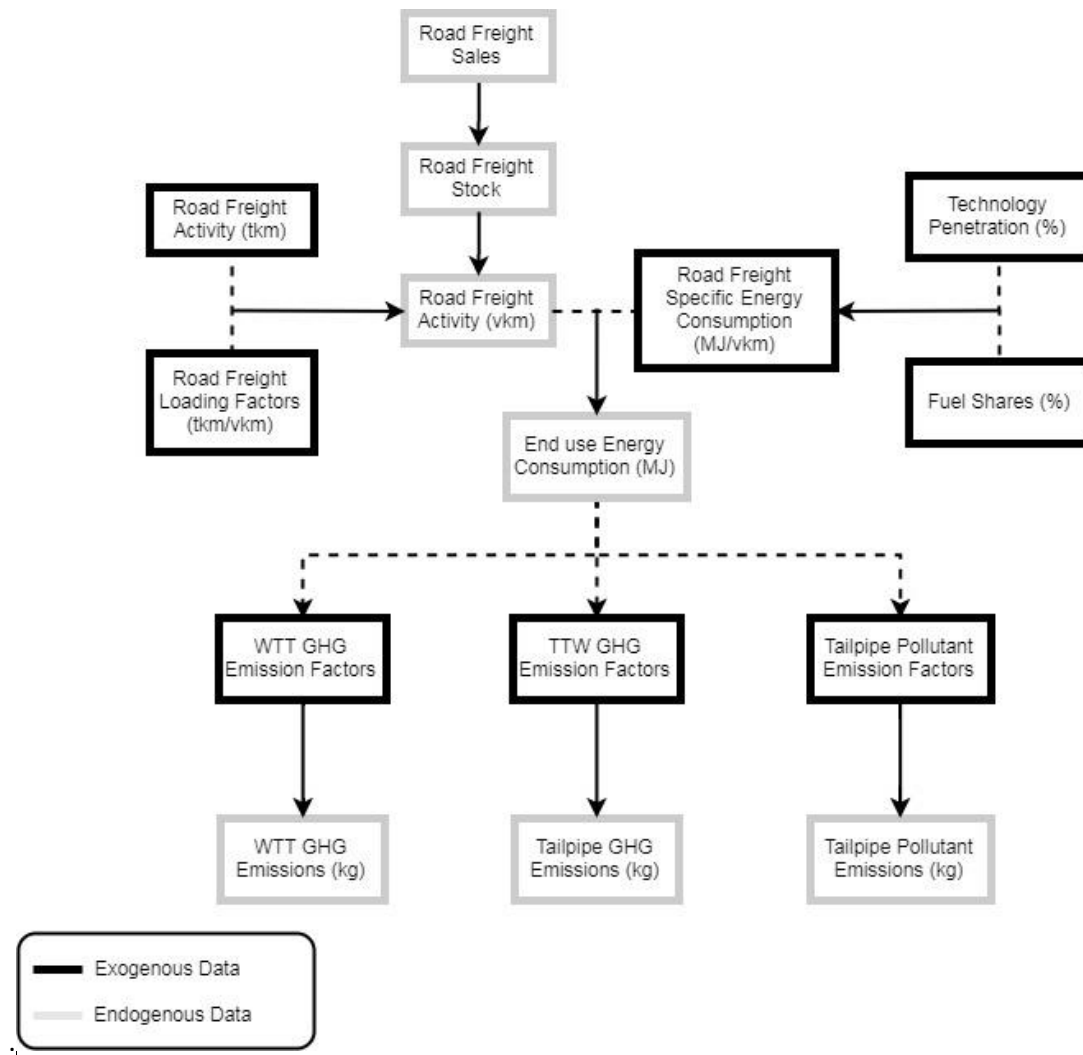


Figure 2.2: Flow diagram of MoMo's road freight module

In the case of stock, different types of trucks are used for different purposes, e.g., long-haul vs. short-haul deliveries, and there are different technology options available for these classifications.

To account for these variances, MoMo splits road freight vehicles into the following categories:

- Light-commercial vehicles (LCVs) with a gross vehicle weight (GVW)⁴ less than 3.5 tonnes (t).
- Medium-freight trucks (MFTs), commercial vehicles with a GVW from 3.5 t to 15 t.
- Heavy-freight trucks (HFTs), commercial vehicles with a GVW greater than 15 t.

The calculation of stock is carried out as follows: Total freight tkm and vkm are first projected based off a linear multi-variate regression model using a range of national historical data points and driven by a combination of variables identified to influence freight activity (later described in Section 2.3).

This freight activity is split into the contribution from MFTs and HFTs based on separate regressions,

⁴ The GVW is defined as the maximum recommended operating weight of a vehicle – including the vehicles chassis, body, engine, fuel, driver/passengers and cargo – as specified by the manufacturer

with LCV based on a GDP/capita logic.⁵ Projections of mileages are based on historic values within MoMo, allowing for the calculation of stock when paired with vkm data. Sales data is subsequently calculated through an allocation of stock based on age. Technology penetration in new vehicle sales is entered into the model exogenously, differentiated by region and informed by cost comparisons contributing to the formation of scenarios.

In this chapter, policy measures are introduced to generate the RTS and the MTS, whereby the development of energy efficiency, mileage, load factors, fuel types, and technology shares in new vehicle sales are modified to explore the two potential pathways for the future of the road freight sector to a time horizon of 2050.

2.3 Key Drivers of the Road Freight Sector

Economic growth has been identified as a strong driver of the rise in road freight activity (Eom et al., 2012, IPCC, 2014b), however there are a number of other contributing factors such as the availability of commodities (Kamakaté and Schipper, 2009, Whyte et al., 2013), fuel prices (Edelenbosch et al., 2017), and road infrastructure (Engström, 2016). This section reviews a number of the primary drivers which may influence global road freight activity, for which both historic and projected data was available, intending to add to literature which considered national and regional trends, such as Kamakaté and Schipper (2009) and Mendiluce and Schipper (2011). In adhering to this criterion, this review considers the regional variables of income (proxied by purchasing power parity gross domestic product (GDP PPP) per capita); gross value added to the agriculture, commercial, and industry sectors; fuel prices; population; population density; country/region size⁶; and level of infrastructure. The remainder of this section provides background on the data available, and then discusses the historic trends found with these drivers at a regional/country-level basis.

2.3.1 Data Availability

The projections used in this study were based on the creation of a wide-ranging dataset of historical road freight activity across as many regions as possible, and using a regression analysis to determine the underlying factors that drive this sector, which in turn can be used to create more accurate activity projections. Little publicly available data exists on freight activity, especially in developing

⁵ There were a low level of data points relating to LCV activity, relative to its MFT and HFT counterparts, thus limiting the regression in this study to the latter two truck classifications

⁶ MoMo aggregates countries into 43 regions, thus the freight activity of some countries are only calculated at a supra-national level

regions such as Africa, the Middle East, and the non-EU Eastern Europe/Eurasia region. Although many OECD member countries report their national tkm on an annual basis, the methods for estimating road-freight activity are not uniform, and are subject to revision in certain countries. China, for example, significantly changed the coverage of its on-road freight survey in 1985, and then again in 2008 (MOT, 2010).

Due to the low level of data coverage in certain regions, this study relies on informed estimations in the determination of key energy demand indicators. To calculate energy demand and resulting pollutants, key assumptions have been adopted in relation to load factors and truck-size split. This study combines national reported data of 1900 observations for tkm, 490 observations for vkm, and 413 observations that split tkm by truck size for MFTs and HFTs over the period 1971-2014. These observations are at a country level, later aggregated by region. A full list of these sources with a corresponding number of observations can be found in Appendix A.

2.3.2 Road Freight and National Economic Activity

A strong correlation was found to exist between country- and regional-level GDP per capita and per capita levels of road freight activity.⁷ This correlation was established using the collected national reported data for freight activity, and accounts of national GDP and population taken from the OECD and UN's respective databases with coverage of 214 nations over the period 1970 to 2015 (OECD, 2016, UN, 2016).

The global long-run elasticity of road freight tkm per capita to GDP per capita is close to unit elastic (1.06) and the response to GDP per capita of vehicle activity (vkm per capita) is similar (1.04). Activity of HFTs is relatively more elastic than that of MFTs with respect to GDP per capita, with elasticity values of 1.42 and 0.49 respectively.⁸ This implies a shift in activity from MFTs to HFTs as GDP per capita increases, a trend that may be explained by the fact that, in general, as an economy develops, so too are logistics improved and infrastructure developed, leading to a structural shift to larger trucks. In contrast, in low-income countries road freight is dominated by smaller trucks, which are able to operate on more constrained road infrastructure that is incapable of supporting larger truck sizes (IISD, 2013).

⁷ All variables, with the exception of normalized fuel prices and country and regional area, dummies were log transformed in the regressions used to project freight activity based on historical trends. Hence, the coefficients on the GDP per capita variable directly yield elasticity estimates

⁸ The availability of truck disaggregation by GVW is largely limited to the United States and the 28 European Union member states (see Appendix A)

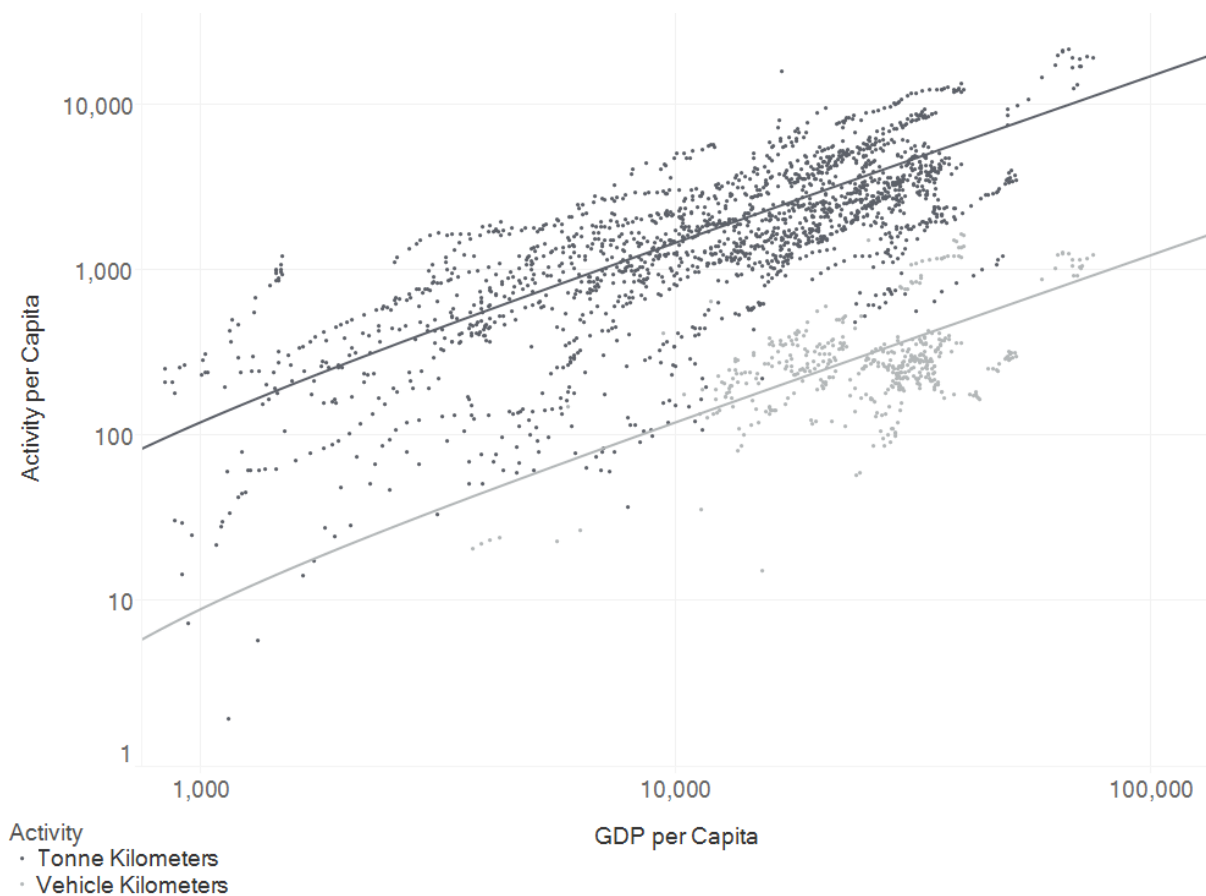


Figure 2.3: Regional road freight activity per capita vs. GDP per capita. Source: see Appendix A

There is growing attention to the evidence supporting the conjecture that road freight activity might start to decouple from economic growth. National statistics suggest that at high income levels, economic growth might not correspond with commensurate (near unit elastic) growth in freight activity, but that activity might instead level off or decrease at high levels of GDP per capita. There are a few cases which suggest that this decoupling has begun in developed regions. In Japan, activity declined between 2005 and 2015 (Japan Statistics Bureau, 2011, Japan Statistics Bureau, 2017), partly due to stagnating economic growth during the mid-1990s following the economic collapse, but this may also be partly attributable to improvements in domestic logistics and operations. In the United Kingdom, freight activity remained flat from 1997-2004 while the economy grew (McKinnon, 2007). Most of this apparent decoupling could be attributed to the growing presence of foreign firms in the United Kingdom's road freight, a decline in road freight's share of overall freight activity (i.e. a modal shift), and increasing prices for road freight services. Spain and the United States also witnessed some degree decoupling of economic growth and road freight activity between 1999 and 2007 (Alises et al., 2014, Caid, 2004). Just as in the United Kingdom, the decoupling can mainly be attributed to the growth in the share of services to value added, although, in the case of Spain,

decoupling was found to be less pronounced due to less marked improvements in logistics and supply chain management than in the United Kingdom.

However, on a global scale, when tracking historical developments, this study does not find strong evidence that decoupling is occurring, corroborating the findings of Eom et al. (2012) and De Jong (2016). Despite this finding, the projections adopted here do account for a slight degree of decoupling, occurring only at high-income levels, in order to reflect the growth of economic output imputable to services and the declining share in value added of freight transport-intensive economic sectors like industry and agriculture.

2.3.3 Fuel Price Effect

Fuel taxation has the potential to act as a policy lever in controlling the level of freight activity at a national level. Increasing taxes on petroleum-based fuels can act as an incentive for freight operators to focus on improving logistics and operational efficiency, although rising prices for freight operators might also be passed on in the form of a higher prices for the consumer, resulting in less elastic responses to fuel price fluctuations, as seems to be the case in the United States (Winebrake and Green, 2017, Winebrake et al., 2015) . If these prices cannot be passed onto the consumer, or would result in a substantial reduction in demand, the freight operator might be incentivised to promote the utilization of vehicle capacity to prevent a reduced profit margin. In India, for example, diesel prices surged in 2012 and some truck operators claimed to be unable to increase freight rates due to stiff competition and low bargaining capacity between truck operators and brokers (IISD, 2013).

Using normalised fuel price⁹ as an explanatory variable for freight activity, the correlation of normalised fuel price on road freight tkm per capita was substantially less pronounced in non-OECD regions than that of OECD regions, potentially reflecting the fact that fuel price is a more effective lever to control freight activity in developed economies. While fuel price may act as a policy lever to reduce trucking freight activity in developed regions through encouraging logistic management improvements, some studies indicate that a substantial increase in fuel prices would not force a modal shift from trucking towards rail or waterways and only has substantial effects in its own sector (Beuthe et al., 2001, Schade et al., 2008).

⁹ Fuel prices taken from the OECD database are normalised against the year-on-year highest global fuel price in this regression analysis

2.3.4 Demographic, Topographic and Infrastructural Effects

In theory, goods can be transported by any number of freight transport modes; the vast majority of goods are moved by maritime, road, rail, and waterways, with a small but rapidly growing percentage of air freight. The mode ultimately taken is directly dependent on two main considerations: shipping cost and timeline of delivery (which is particularly crucial for perishable goods). These, in turn, are dependent upon a mix of variables, including socio-demographics, topography, and infrastructure available to a region. While the former two are not easily modified by policy, infrastructure availability depends on a country's governance, including historical investments and regulations. For example, the Staggers Railway act of 1980 in the US allowed for a loosening of the regulations on the railway freight sector and in turn increased profitability within this industry allowing for substantial investments into the improvement of the rail network (Office of Rail Policy and Development, 2011).

Population dense regions, such as India's major cities, tend to have a high reliance on road freight for 'last-mile' deliveries, while in countries with a wide spread and sparse population (as, for instance, in Russia), the competitiveness of rail transport for goods transportation tends to be advantaged. The modal share of freight transportation has fluctuated over previous decades, driven predominantly by changes in the type of goods transported, geographic scope (i.e. international/domestic transport), and the level of policy support and infrastructure pertaining to competing modes of freight. For example, the share of rail freight increased in Mexico and the UK following privatisation of the rail sector in the mid-1990s, marking the end of a previous contraction in the decade prior to this (Mckinnon, 2016a).

The regional provision and availability of infrastructure determines the viability of inter-modal goods movement. While a loose correlation is evident between the national/regional level of freight activity by mode and the rail/road infrastructure (further shown in the Section 2.3.5), this link is influenced also by demographics and economics and hence the share of rail activity is not a particularly useful predictor of total road freight tkm.

2.3.5 Multivariate Linear Regression Model Runs

Road freight activity data was first cleaned by removing any internal inconsistencies, such as remarkably high tkm/capita values, and then grouped into the 43 regions corresponding to the geographic resolution of MoMo, reducing the total number of observations. To determine which independent variables might be best suited to explain the variation in road freight activity, several

bivariate regressions were first run in sequence for each of the explanatory variables. The individual significance, intercepts and coefficients of all explanatory variable examined are shown in Table 2.1.

Table 2.1: Regression parameters for individual freight related parameters

Explanatory Variable/Independent Variable	Natural Log of Total tkm per Capita		Natural Log of HFT tkm per Capita		Natural Log of MFT tkm per Capita		Natural Log of vkm per Capita	
	Intercept	Coefficient	Intercept	Coefficient	Intercept	Coefficient	Intercept	Coefficient
Natural Log of Gross Domestic Product PPP per Capita	-3.1	1.11***	4.2	0.38***	0.7	0.51***	-8.8	1.42***
Natural Log of Gross Value Added to Industry per Capita	-1.6	1.08***	4.3	0.41***	1.2	0.53***	-5.9	1.30***
Natural Log of Gross Value Added Services per Capita	-1.1	0.94***	5.1	0.30***	2.1	0.39**	-6.1	1.19***
Natural Log of Gross Value Added Agriculture per Capita	9.0	-0.29***	9.4	-0.22*	5.5	0.07	8.8	-0.57***
Fuel Price	6.6	8.3E-03***	8.0	-5.0E-04	6.5	-4.7E-03***	5.8	-1.7E-03**
Normalised Fuel Price	6.0	2.19***	9.2	-1.63***	7.6	-2.2E+00***	3.1	3.12***
Country Area	7.1	6.3E-08***	8.0	1.4E-07***	5.8	1.4E-07***	5.1	2.0E-07***
Population	7.2	-4.0E-10*	8.0	2.2E-09**	5.8	2.6E-09**	5.1	4.2E-09***
Population Density	7.1	5E-04	8.2	-1.1E-03**	5.8	4.0E-04	5.3	1.3E-04
Natural Log of Rail Tkm	7.3	3.3E-07**	8.0	5.0E-07***	5.9	5.7E-07***	5.5	7.5E-07***
Road Infrastructure	7.0	3.4E-07***	7.9	1.8E-07***	5.9	1.5E-07**	5.1	3.6E-07***
Rail Infrastructure	7.2	3.8E-06***	8.0	2.5E-06***	5.9	2.3E-06***	5.4	3.9E-06***
Road – Rail Tkm Ratio	7.3	9.8E-03**	8.1	-3.6E-04	6.0	-2.6E-03	5.6	3.0E-04
Road – Rail Infrastructure Ratio	7.1	5.2E-03*	8.2	-5.4E-03	6.2	-0.01*	6.4	-0.04***

*** p < 0.001

** p < 0.01

* p < 0.05

blank p < 1

Next, a range of multivariate regression forms were run, and results were compared in terms of their explanatory power and degree of intuitive plausibility. The regression chosen for projections used the explanatory variables of GDP per capita, normalised fuel price, and a size factor based on total country/region area (see Table 2.2). Long-term activity projections and back-cast estimates were determined for total tkm and vkm using this regression and the calibrated national tkm in 2015 from the MoMo database as an anchor point. Secondary regressions were run with HFT and MFT tkm¹⁰ as separate dependent variables and all of the same independent variables as above. As the number of

¹⁰ LCVs were omitted due to lack of data availability, and the pre-existing method of calculating tkm was adopted for these classes of vehicles

observations of HFT and MFT activity was significantly lower than the total aggregated activity, only the shares of this regression were kept, with the regression of total tkm determining the share of tkm allocated to MFTs and HFTs in each region and future year (see Equation 2.2).

Table 2.2: Regression parameters for combined freight related parameters

	Natural Log of Total tkm	Natural Log of MFT tkm	Natural Log of HFT tkm	Natural Log of Total vkm
Intercept	-1.83***	2.38*	-4.88***	-3.49***
Natural Log of GDP per capita	1.06***	0.49***	1.42***	1.04***
Normalised Fuel Price	-0.82***	-0.72**	-2.34***	-0.99***
Size Factor	-0.36***	-1***	0.33+	-0.81***
R ²	0.81	0.93	0.89	0.93
N	492	69	69	98

*** p < 0.001

** p < 0.01

* p < 0.05

+ p < 0.1

$$tkm_{s,r} = \left(\alpha_{0,T} + (\alpha_{1,T} * \ln(\frac{GDP_r}{Pop_r})) + (\alpha_{2,T} * NFP_r) + (\alpha_{3,T} * SF_r) \right) \frac{(\alpha_{0,s} + (\alpha_{1,s} * \ln(\frac{GDP_r}{Pop_r})) + (\alpha_{2,s} * NFP_r) + (\alpha_{3,s} * SF_r))}{\sum_{n=s}^S (\alpha_{0,n} + (\alpha_{1,n} * \ln(\frac{GDP_r}{Pop_r})) + (\alpha_{2,n} * NFP_r) + (\alpha_{3,n} * SF_r))} \quad (2.2)$$

Where α_0 is the intercept of a regression for the activity of a truck of size ‘s’ out of ‘S’ sizes (MFT or HFT) in region r defined by the coefficients α_{1-3} (described in Table 2.2) and the explanatory variables of GDP per capita, normalised fuel price (NFP), and a binary size factor (SF). The share of MFT or HFT tkm was scaled up by the regression of total tkm ‘T’. Each of these projections were subsequently benchmarked off the last year of data available, if any, for each country/region. Road freight vehicle movements are typically measured in vehicle-kilometres (vkm), a metric that measures the total annual distance covered by a given rolling vehicle stock. Given the limited availability of vkm statistics, vehicle activity is more difficult to estimate at a global level. Despite data availability limitations, regressions of vkm per capita and GDP per capita clearly confirm that vehicle activity, like freight activity (tkm), grows with rising incomes. Assumptions and estimations were adopted to overcome some of the data limitations. Vehicle activity at the country and regional levels was evaluated here based on the ratio of tkm and average vehicle load (expressed in tkm/vkm), building on the available statistics on tkm and on an assessment of the representative loads for each truck category (LCVs, MFTs and HFTs). All representative loads include empty running:

- LCVs, primarily used for last-mile deliveries, are assumed to operate with an average load of 0.5 t. This is consistent with load carrying capacities in the range of 1 t to 2 t, shares of empty running in the 40% to 60% range and capacity utilisation rates on laden trips in the 50% to 60% range.
- MFT loads are assumed to range between 4 t and 10 t and to decline with increasing income (Figure 2.4, [a]). This assessment builds on indications derived from surveys that focus on truck loads in developing regions (Grütter, 2016) and statistics on loads and gross vehicle weight published for OECD countries, including data for the United States (BTS, 2015) and countries in the European Union (Eurostat, 2016).
- Loads for HFTs are assumed to fall in the 12 t to 16 t range. These loads are also assumed to rise with income, reflecting the evolution of gross vehicle weights with income growth observed in the European Union (Figure 2.4, [b], based on Eurostat (2016)). This is consistent with a shift to tractor-trailers and combination trucks in high-income countries (over rigid trucks), the relaxation of constraints on longer and heavier vehicles, and road network improvements.



Figure 2.4: Freight load curves for MFTs [a] and variance in GVW for HFTs [b]

2.4 Low Carbon Options for Road Freight

This section presents the opportunities available for decarbonising road freight. These include specific policies and incentives that could affect the long-term outlook for road freight transport, namely measures to (i) improve the energy efficiency of trucks, (ii) spur improved logistical systems,

and (iii) increase investments in supply infrastructure and vehicles technologies to shift to alternative fuels, all of which are adopted to some degree in the RTS, consistent with the need to ramp up policy and technology developments in the road freight sector in order to achieve the Nationally Determined Contributions (NDCs).¹¹

The same three categories of measures are adopted much more quickly and to a greater extent in the MTS. This scenario focuses on the ambitious but attainable deployment of technologies, policies and innovative business practices that deliver the same services as in the RTS but with radically reduced vehicle activity, less overall movement of goods, and reduced energy demand and emissions. The remainder of this section focuses on these three categories of measures to reduce the energy and emissions of road freight and their role in the RTS and the MTS.

2.4.1 Energy Efficient Technologies

The ranges of the potential for technical and operational efficiency investments that pay for themselves from the perspective of the truck operator within three years over the 2015-30 timeframe have an average value of about 23% (Schroten et al., 2012) albeit with wide variations among vehicle missions and types; there is generally a greater potential for savings in HFTs than in MFTs. Table 2.3 outlines engineering literature estimates on the range of commercially available efficiency technology options in road freight vehicles.

Vehicle design improvements that reduce energy needs include improvements in aerodynamics, reduced rolling resistance for tyres and truck weight reduction. Enhanced powertrain efficiency can be realised via improvements to the engine, transmission and drivetrain – powertrain controllers that integrate transmission and engine controls can bring additional fuel savings. Battery-powered electric auxiliary power units can provide on-demand power for climate control and other cabin devices while saving fuel.

¹¹ The NDCs would lead to an emissions trajectory across the energy sector corresponding to an estimated 2.7 degree increase in global average temperature by 2100 (IEA, 2017a). RTS is developed within MoMo and assesses the outlook for energy demand and emissions growth from road freight transport by considering all relevant policies and measures that are already adopted today or have been announced, even when the precise targets have yet to be fully defined

Table 2.3: Energy efficiency measures for road freight

Measure	Description	Potential energy Savings	Source
Aerodynamics	A wide range of aerodynamic fittings can reduce the drag coefficient, thereby reducing road load.	Individual vehicle components reduce fuel use by 0.5-3%, depending on the truck type and aerodynamic retrofit.	(Schroten et al., 2012, Mannix, 2015)
Low rolling resistance (LRR) tyres / Tyre pressure systems (TPS)	LRR tyres can be designed with various specifications, including dual tyres or wide-base single tyres with aluminium wheels, and next generation designs.	The potential ranges from about 0.5% to 12% in the tractor-trailer market. TPS alone could reduce fuel use by 0.5-2%.	(Meszler et al., 2015, Schroten et al., 2012, Mannix, 2015, Hill et al., 2015)
Light-weighting	Broadly, all HDV vehicle types except utility trucks could cost-effectively reduce weight by upwards of 7% within the next ten years.	The CO ₂ savings potential is about 1% by 2020, 2-3% by 2030 and 2.7-5% by 2050.	(Hill et al., 2015)
Transmission and drivetrain	Moving from manual to automatic/automated manual transmission can greatly improve efficiency. Adding gears, reducing transmission friction and using shift optimisation in manual automated or fully automated transmissions can also improve drivetrain efficiency.	Automatic/automated transmissions reduce fuel consumption by 1-8%, depending on truck type; other improvements lead to fuel savings of about 0.5-2.5%.	(Schroten et al., 2012)
Engine Efficiency	Engine improvements include increasing injection and cylinder pressures, both of which typically improve incrementally on a yearly basis.	Improvements in the coming decade could lead to fuel savings of approximately 4% (in service/delivery vehicles) to 18% (in long-haul).	(Schroten et al., 2012)
Idling reducing technologies	These include auxiliary power units and generator sets, battery air conditioning systems, plug-in parking spots at truck stops and thermal storage systems.	As much as 2.5% of the fuel consumed by road trucks may be due to idling operations. As such, this is an upper threshold on the potential fuel savings (energy savings are less).	(ANL, 2013, Van Lier et al., 2010)
Hybridisation	Electric hybridisation tends to be the best hybridisation option for most other mission profiles.	Dual-mode hybrid: 8-30% Parallel hydraulic hybrid: 15-25% Parallel hybrid: 6-35% – all ranges depend on vehicle type.	(Law et al., 2011, Schroten et al., 2012)

Note: For further details, see (IEA, 2017b).

2.4.2 Measures to Improve Road Freight Systems Efficiency

Achieving deep decarbonisation in the road freight sector, along a trajectory consistent with the IEA Energy Technology Perspective's Beyond Two Degree Scenario (B2DS) (IEA, 2017a), will require the near complete realisation of all of the systemic improvements of which only a subset are partially realised in the RTS. In addition, measures that require closer external collaboration across firms, including sharing of assets and services between and among companies, as well as more radical re-envisioning of how logistics systems operate, are needed to bring road freight emissions in line with B2DS emissions targets. Policies that reward efficiency and collaboration, as well as regulations and/or pricing measures to discourage 'just-in-time' and same- or next-day deliveries and other similar practices that constrain the flexibility of supply chain operations, will be needed to drive the radical changes needed to reduce the GHG footprint of road freight. A list of methods of systems efficiency improvements is outlined below.

Table 2.4: Improvement in road freight logistic measures

Measure	Description	Truck Type Affected	Parameters Affected	RTS Potential Realised in 2050	MTS Potential Realised in 2050	Source
Optimised Routing	Optimising delivery routes using GIS plus real-time routing data enables both time and fuel savings for both intra-city trucking and long-haul missions	All LCVs, MFTs, HFTs	Activity (vkm)	3.2%	4.5%	(Carbon War Room, 2012)
Platooning	Gaps between trucks driving on highways can be reduced using smart vehicle communication and automation (CAV) technologies, which reduces drag and thereby reduces fuel consumption	Non-urban MFTs, HFTs	Energy intensity (MJ/vkm)	7.3%	11.3%	(Tsugawa et al., 2016)
Improved Vehicle Utilisation	Optimisation of loads carried can be achieved both via internal logistics improvements and through external (i.e. across-firm) collaboration	All LCVs, MFTs, HFTs	Utilisation (load factor)	5.4%	9.0%	(Collaborative Concepts for Co-modality, 2013)
Back Hauling	Backhauling is a specific case of improving vehicle utilisation via delivering cargo on return trips, thereby offsetting other trips	All MFTs, HFTs	Utilisation (load factor)	1.9%	3.8%	(Greening et al., 2015)
Last-mile Efficiency	The allocation and prediction of dynamic demand can help to prepare for seasonal and daily peaks. Particularly in congested urban regions, there is a potential for logistics service companies to capitalise on ICT and the sharing economy to more cheaply and efficiently ship goods over the last mile	Urban LCVs and MFTs	Activity (vkm)	2.3%	3.8%	(IEA, 2017b)
Urban Consolidation Centres	By grouping shipments from multiple shippers / retailers and consolidating them onto a single truck for delivery to a particular locality, vehicle activity and emissions within urban centres can be reduced	Urban LCVs and MFTs	Activity (vkm)	0.8%	3.8%	(Allen et al., 2012)
Re-Timing Urban Deliveries	A shift to off-peak deliveries lead to a reduction in local pollutants and improved fuel economy, due to the reduction in congestion	Urban LCVs and MFTs	Energy intensity (MJ/vkm)	2.3%	3.8%	(Holguín-Veras et al., 2016)
Co-modality	Operational efficiency gains come from extending the operations of not only private citizens' trips but also public transit and taxi operations to deliver goods in urban settings	Non-urban MFTs, HFTs	Activity (vkm)	-	3.8%	(Ronald et al., 2016)
Crowd-sourced Logistics	Crowd-shipping is a means of translating the concept of crowd-sourcing to freight and is intended to accommodate last-mile delivery through deploying a wide number of individual citizens as couriers.	Urban LCVs and MFTs	Activity (vkm)	-	3.8%	(McKinnon, 2016a, McKinnon, 2016b)
Co-loading	Co-loading is a means of increasing vehicle utilisation through bundling shipments across product categories with similar shipment parameters (e.g. destination and time constraints).	All MFTs, HFTs	Activity and utilisation	-	7.5%	(Vernon and Meier, 2012)
Physical Internet	The physical internet describes an open, shared, and modular global logistics system inspired by the movement of data on the internet, in contrast to the proprietary logistics systems that are common today.	All LCVs, MFTs, HFTs	Activity and utilisation	-	18.8%	(Sarraj et al., 2014)

Note: For further details, see (IEA, 2017b).

The combined impact of these methods brings about a reduction in road freight activity (tkm) of 13.5%, and a decline in vehicle activity of more than 20% in 2050, relative to the RTS. The difference between the reduction in tkm and vkm is a measure of the impact of improved vehicle utilisation (or

equivalently, of higher load factors, as expressed in tkm/vkm) that can be realised by the above measures. Energy intensity (MJ/vkm) also declines due to more efficient urban operations (resulting from re-timing urban deliveries) and in highway driving due to platooning.

2.4.3 Alternative Fuels and Fuel Technologies

Alternative fuels act as a means of addressing the many near- and long-term economic, societal and environmental dilemmas posed by the continued reliance of road transport on oil. Notwithstanding the opportunities provided by alternative fuels and powertrains to diversify from petroleum-derived fuels as the dominant energy sources for road freight and to decarbonise the sector, they face many challenges, such as high abatement costs (Malins, 2011, Holland et al., 2015). This section highlights four alternative energy carriers that could be used in road freight in a low-carbon future: natural gas, biofuels, hydrogen, and electricity.

2.4.3.1 Natural Gas

Medium and heavy-duty compression ignition engines can be designed to run on a blend of diesel fuel and methane, where methane is typically mixed with small volumes of diesel to provoke ignition. Alternatively, engines can be manufactured to run solely on methane, using positive (also known as spark) ignition systems. Natural gas is the main source of methane currently available and used in dual fuel and dedicated engines. However, the GHG mitigation potential of switching to natural gas trucks is limited – even if upstream leakage issues are addressed and the best available vehicle technologies are adopted, WTW reductions relative to diesel ICE trucks are limited to about a 20% improvement at most (DBI, 2016, Dominguez-Faus, 2016, JRC, 2014),¹² and this is insufficient in the context of the mitigation ambition of the Modern Truck Scenario. Bio-methane, with similar physical and chemical properties to fossil natural gas, can be used in the form of compressed natural gas (CNG) or liquified natural gas (LNG), and when produced by upgrading raw biogas produced via anaerobic digestion of high moisture content organic wastes, can deliver substantial GHG benefits on a WTW basis.

2.4.3.2 Biofuels

A range of biofuel options have potential to reduce oil demand from heavy-duty road transport, with the case for their use strengthened due to their high energy densities, and for several fuels also their compatibility with existing vehicle fleets and fuel distribution infrastructure. Production processes

¹² Studies that consider current performance of engine technologies find that fossil natural gas provides no net reduction in WTW GHG emissions from trucks (JRC, 2014; IEA-AMF, 2016), though there is a high degree of variability and uncertainty in these comparisons (Dominguez-Fauz, 2016)

for biofuels are technically mature, with heavy-duty vehicles suitable for their use available from major original equipment manufacturers (OEMs). There are a variety of low-carbon, advanced biofuel feedstocks and production pathways which may serve as a potential fuel source for freight in the future. The most promising are summarised here:

- **Bio-diesel** can be produced from a range of feedstocks and is most commonly in blending form below 20% (B20). Higher blends such as B50 or pure bio-diesel (B100) can also be used but require technical modifications to freight vehicles.
- **Hydrotreated Vegetable Oil (HVO)**, also known as renewable diesel, can be produced from a similar range of feedstocks as bio-diesel and can be used unblended (HVO100) without modifications to heavy-duty diesel engines or changes to fuelling infrastructure.
- As outlined above, **Bio-methane** can be used in natural gas fuelled vehicles.

The main barrier facing biofuels adoption is their long-term economic competitiveness relative to highly volatile oil prices (which translates, albeit imperfectly, to volatile pump prices for automotive gasoline and diesel fuels). Even if certain biofuel pathways manage to become economically viable, from a climate and sustainability perspective there is likely to be a limited volume of feedstock that does not compromise food, land, water, and soil resource availability (Slade et al., 2014). Moreover, in a context of commitment to decarbonisation targets, competition for use of biomass resources within the energy sector is likely to favour their adoption not only in road freight, aviation, maritime, but also in industrial and power applications (i.e. BECCS) (IEA, 2017a). Despite these considerations, advanced and low-carbon biofuels are likely to be needed, particularly in the coming few decades, as a bridge from the current fossil dependent infrastructure undergirding road freight to the new infrastructures needed for ultra-low and zero-emission energy carriers, such as hydrogen and electricity.

2.4.3.3 Electric Trucks

Relative to a typical ICE engine, the efficiency of battery electric motors is significantly higher, although the greater size and weight of trucks relative to light-duty vehicles substantially increase the barriers to batteries to serve as a substitute for diesel in the road freight sector. The key performance considerations for batteries designed for use in electric trucks are gravimetric and volumetric energy density, the specific power (W/kg), the durability and number of discharge cycles a battery can undergo before losing too much capacity, temperature management requirements, and safety. The hurdles to electrification are lower for trucks with lower GVW and shorter annual mileages and so plug-in and battery electric LCVs and MFTs in urban contexts are beginning to move

into the early deployment phase, while greater barriers must be overcome within HFTs due to the nature of their size.

Due to the cost implications of large battery requirements, the challenge for the electrification of trucks, particularly in the HFT segment, is one of how to reduce battery needs through the supply of electricity to vehicles while in motion. Electric road systems (ERS) enable vehicles to receive electricity from power transfer installations along the road upon which the vehicles are driving. Vehicles using ERS can be hybrid, battery-electric, or hydrogen fuel cell vehicles and can conduct normal driving operations, such as overtaking and driving autonomously, outside of ERS-enabled lanes. The main infrastructure concepts for ERS are:

- **Conductive power transfer**, which may take the form of overhead catenary lines, which requires the installation of an overhead retractable pantograph on trucks; or of in-road conductive charging, which requires the installation of a connection arm under or behind the truck.
- **In-road conductive charging**
- **Inductive transfer of power**, requiring the installation of coils that generate an electromagnetic field in the road as well as receiving coils for electricity generation on the vehicle.

2.5 Model Results

This section applies the drivers identified in Section 2.3 in tandem with the low-carbon options from Section 2.4 to present two scenarios, the RTS and the MTS. The former presents the outlook for future energy demand and GHG emissions growth to 2050 based on all policies affecting the outlook for road freight transport and those that have been announced and are expected to take effect in the near future. This establishes an ambitious reference scenario of how road freight activity, energy demand, and emissions trends would develop if nations begin to integrate sectoral specific policies with their broader NDC commitments. The latter scenario lays out a modernisation strategy for future road freight transport which aims to overcome the shortcomings identified in the RTS in terms of selected principal energy policy objectives, most prominently energy security and climate change. It envisions rapid adoption of the technological and system-wide measures for reducing the sector's future energy and emissions growth and lays out the benefits of this approach from an energy and climate policy perspective. It further identifies the key policy requirements for realising such a scenario.

2.5.1 Freight Activity

2.5.1.1 Reference Technology Scenario

Global growth in road freight activity per capita broadly mirrors per capita GDP growth, and so rapid economic and population growth in emerging and developing economies results in a growing share of global tkm in these countries. In the RTS, the contribution of HFTs also increases over time; by 2050, three-quarters of global road freight activity is covered by HFTs, up from 63% today, which reflects the continuation of a structural shift from MFTs to HFTs accompanying the development of highway infrastructure (and secondarily to LCVs as urban delivery operations develop).

Consequently, the share of road freight activity serviced by MFTs declines from one-third today to 20% of the total in 2050.

Overall global road freight tkm grows by 2.4-fold over the period 2015-2050 in the RTS with the majority of growth attributable to developing countries, concomitant with economic growth. Developing countries account for 75% of road freight activity in 2050. China has the most road freight activity in the world in 2050, while India has the fastest level of growth at 5.6% per annum. Africa also experiences substantial growth, with road freight activity expanding 4-fold from 2015 to 2050, although the low base of current activity means that in 2050 the region accounts for only 10% of global road freight activity. Growth in freight activity is dampened by measures identified to improve logistics and streamline supply chains, shown in Table 2.4, while improved utilisation of vehicles results in increasing average truckloads.

2.5.1.2 Modern Truck Scenario

Road freight tkm in the MTS are reduced by 13.5% relative to the RTS, due to trucks achieving the full potential of systemic measures, as public policy makers and businesses together aggressively pursue the creation of a framework that enables external collaboration across and up and down the supply chain (see Table 2.4). Road freight vkm are reduced by 20%, which differs from that of tkm due to improved vehicle utilisation which equates to increases in the average load of trucks. The HFT fleet accounts for 82% of tkm reductions relative to the RTS, with MFTs accounting for 17%.

Reduction of tkm within the LCV class are negligible as reductions in vkm and increases in the load factor offset each other. The reductions in vkm due to improved vehicle utilisation are roughly equal across all classes of trucks.

2.5.2 Stock Projections

2.5.2.1 Reference Technology Scenario

The global stock of all trucks grows significantly over today's level in the RTS from 2015 to 2050 to support the rise in freight activity:

- The HFT stock increases by 2.6-fold to 64 million vehicles.
- The MFT stock increases by 60% over its current level, to more than 50 million vehicles.
- The LCV stock increases by 65%, reaching around 220 million vehicles.

Trucks remain almost entirely powered by fossil fuels in the RTS. The current absence of large scale deployment efforts beyond initiatives to support the build-up of some refuelling infrastructure mean that the use of natural gas in the RTS remains confined to countries where a substantial cost gap exists between natural gas and diesel and where sufficient infrastructure for natural gas transmission is already in place, such as the US and China. The use of conventional hybrid trucks grows, particularly in LCV fleets operating in urban environments and on regular routes and missions, followed by MFTs and HFTs with regional and long-haul missions. The rate of fuel economy improvements is greatest in developed regions and rapidly developing global markets, including, in particular, China, the European Union, Japan and the United States – the four global regions with fuel economy standards either already in place or (in the case of the EU) coming into effect in the coming few years at the time of writing. Across the entire road freight sector, average service efficiency improves most rapidly in developing and emerging economies, reflecting a structural shift from small and relatively inefficient trucks to HFTs. Yet, a vast residual potential for reducing fuel consumption from road freight vehicles but with payback periods exceeding the average length of time truck purchasers tend to consider (3-5 years maximum) remains unexploited in the RTS as, in the absence of further policy support, the deployment barriers remain too significant to be overcome.

2.5.2.2 Modern Truck Scenario

Reduced activity in the MTS leads to a reduction in stock; LCV stock is reduced by 15%, MFTs by 24% and HFTs by 25% by 2050 relative to the RTS. Increasing technology maturity, infrastructure rollout, and other low-carbon alternatives (especially electricity) make increasing inroads in the MTS. The uptake of alternative powertrains varies by vehicle segment; hybridisation and electrification proceed most rapidly in the urban MFT fleets as both technologies can more effectively realise efficiency gains in short- to mid-distance transient operations. Hybrid trucks enter the truck fleet rapidly: by 2050, within the truck fleet, 7% of LCVs, 40% of MFTs and around 30% of HFTs use hybrid powertrains. The market share of plug-in hybrid electric (PHEV) and battery electric (BEVs) trucks

also grows. In the MTS, three-quarters of LCVs and 35% of MFTs are plug-in (or, in the case of MFTs, catenary-enabled) hybrid or battery electric by mid-century. In addition, 36% of HFTs are catenary-enabled electric trucks. In the modelled scenarios, PHEVs and BEVs dominate in terms of technology uptake, and trucks running on hydrogen fuel cells do not penetrate new vehicle sales in significant volumes due to the greater resilience of cost assessment to variations in assumptions and the more concrete prospects for cost reductions on batteries, given the increasing interest and uptake of electric mobility in light-duty vehicles.

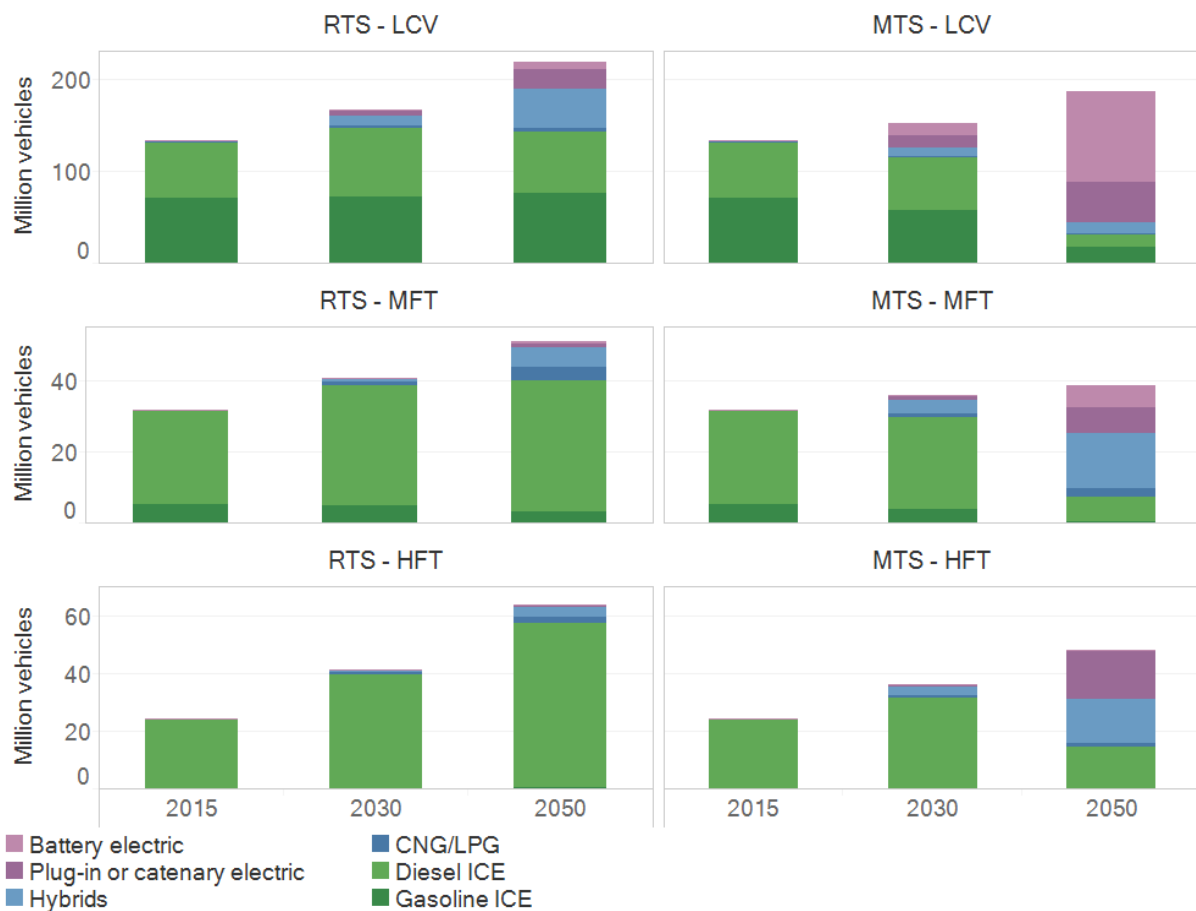


Figure 2.5: RTS and MTS stock disaggregated by truck type

2.5.3 WTW GHG Emissions

2.5.3.1 Reference Technology Scenario

In the RTS, the combined deployment of logistics improvements, vehicle efficiency technologies, and low-carbon fuels constrains emissions growth from the road freight sector. Although total activity grows almost threefold, final energy demand increases by 47% and WTW GHG emissions increase by 55% between 2015 and 2050 to 53 EJ and 4.8 gigatonnes of CO₂ equivalent (Gt CO₂eq) respectively in 2050, indicating a degree of decoupling between both energy and emissions and activity growth.

Without the intervention of any systemic measures, fuel consumption would rise to 63.4 EJ, with the increase over 2015 largely attributable to HFTs outside of the US and EU28 (see Figure 2.5) Despite the developments in the RTS, by 2050, road freight vehicles are responsible for 36% of transport-related GHG emissions, up 3 percentage points from 2015. Practically all the increase in road freight fuel demand in the RTS comes from emerging and developing countries. In the RTS, with 85% of GHG emissions growth between 2015 and 2050 coming from the increased activity of HFTs, which primarily fills the niche of regional and long-haul delivery services. MFTs make up 15% of the emissions growth and the emissions of LCVs remain essentially flat at a global level.

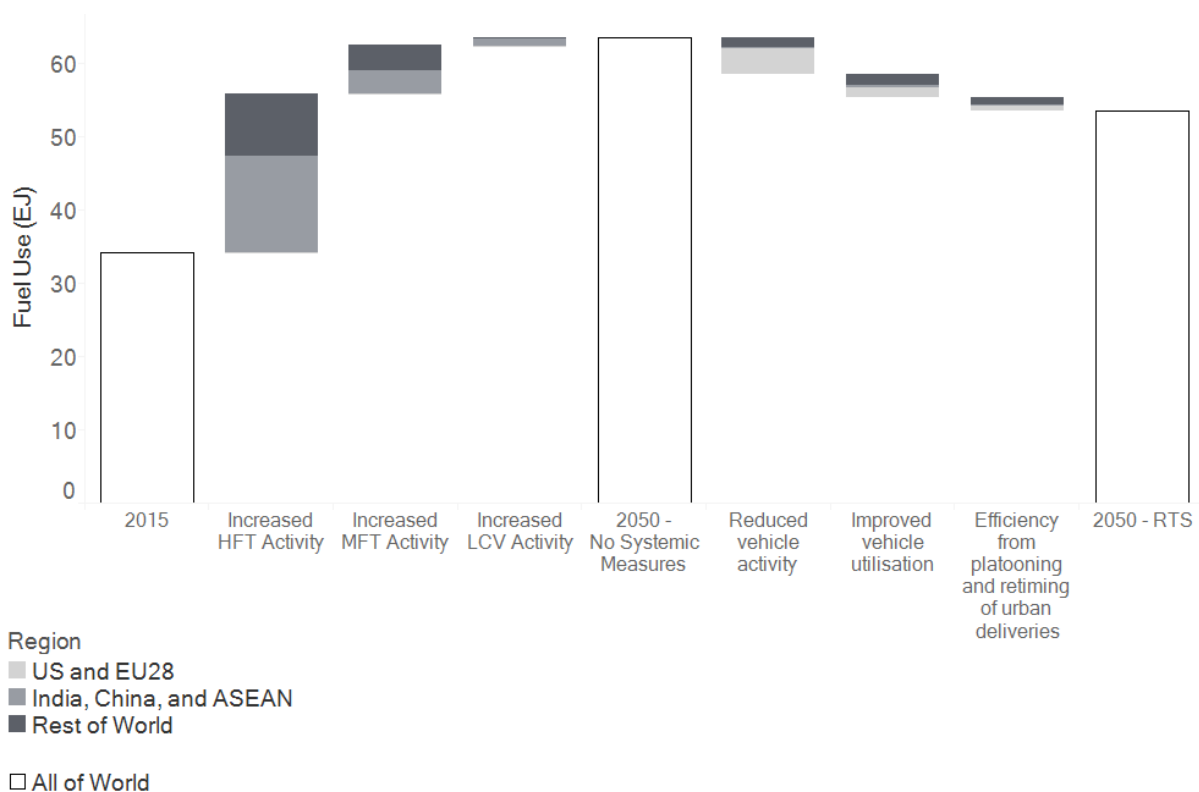


Figure 2.6: Freight fuel use change in the RTS, with and without measures

2.5.3.2 Modern Trucking Scenario

A combination of efficiency measures, systemic improvements in the supply chain and a switch to alternative fuels and alternative fuelled trucks contribute to reductions in WTW GHG emissions in the MTS by 2050 of 60% relative to 2015 and 74% relative to the RTS in 2050. Increasing efficiency at the level of individual road freight vehicles is the most effective overall measure in contributing towards this reduction, responsible for 30% of GHG emission reductions relative to the RTS. The contribution of each of these measures relating to CO₂eq emissions reduction is shown in Figure 2.7.

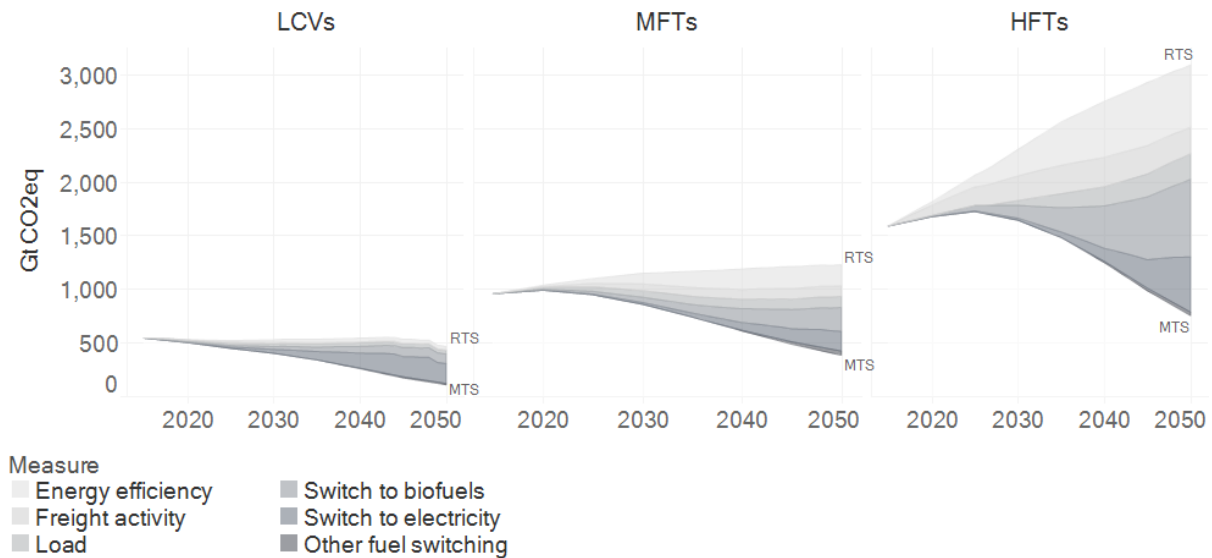


Figure 2.7: Truck contributions to GHG emissions reductions by measure in the MTS relative to the RTS

The vehicle efficiency improvement of the scenario meets the 35% improvement goal (against a 2015 benchmark) recently announced by the Global Fuel Economy Initiative (GFEI) for 2035 and includes further improvements in the subsequent years. The improvement rate is greatest in developed regions and rapidly developing global markets, including, in particular, China, the EU, Japan and the US. In these countries and regions, new HFTs consume just more than half of the final energy in 2035 compared with vehicles entering the markets 20 years earlier, while the energy intensity of MFTs (per vkm) is 40-45% lower. Rapid improvements in these countries and regions reflect their greater wealth and higher relative capacity to invest in efficiency technologies and alternative fuels infrastructure and vehicle technologies that necessitate high capital expenditures, but nearly all of which have payback periods ranging from a few months to just over a decade.

Near complete realisation of all potential systemic improvements identified in Table 2.4 contribute to an 18% reduction of cumulative GHG emissions relative to the RTS due to a reduction in freight activity, and a 12% reduction in cumulative emissions due to increased truck loading. The rollout of these systemic improvements is facilitated through policies that reward efficiency and collaboration as well as price signals and other mechanisms that internalise the externalities associated with road freight transport.

The adoption of biofuels contributes towards 25% of cumulative GHG emission reductions relative to the RTS. Advanced biofuels penetrate the liquid fuel pool rapidly in the MTS, particularly in the short-to-medium term, and displace 6.25 EJ of oil by 2050. Bio-ethanol, bio-diesel and biomethane substitute for gasoline, diesel, and fossil natural gas, reducing GHG emissions of conventional road

freight vehicles. Conventional bio-diesel is gradually phased-out in favour of waste and residue-based renewable bio-diesel (HVO), which by mid-century accounts for 1.5 EJ of road freight fuel. As global supplies of HVO are likely to be insufficient to supply this volume, most of this bio-diesel will have to come from biomass-to-liquid (BtL) processes, which will require further development to improve their efficiency and commercial viability. By 2050, bio-methane supplies nearly 1.1 EJ to road freight. In the MTS, biofuels and Power-to-X together supply nearly 23% of total final energy demand in 2050.

The contribution of ultra-low carbon and zero-emission technologies, modelled here as a switch to electricity (rather than hydrogen) and ERS-enabled trucks, comes relatively late – these technologies begin to exert an impact in 2035 – and the contribution over the entire period is rather small (16%). However, the growing contribution of electricity by mid-century is reflected by the share of the emission reductions it accounts for in 2050 (as opposed to cumulatively from 2015-50): one-third of emission reductions in 2050 come from electrification.

2.6 Conclusions and Policy Recommendations

Road freight transport is one of the largest sectoral consumers of oil which concurrently plays a key role in contributing to economic activity. Regulations to curb the oil demand growth of road freight transport are more limited than passenger vehicles, both in terms of stringency and regional adoption. Fuel economy standards for heavy-duty trucks (including MFTs and HFTs) to date exist only in four countries: Canada, China, Japan and the United States. Current trends appear unsustainable, given that road freight transport appears unlikely to meet key energy policy objectives such as fuel diversification and the reduction of GHG emissions and air pollutants. However, the MTS presented in this chapter presents the policies and technologies that could help to reduce future energy and emissions growth from the road freight sector while ensuring that road freight transport can continue to play its key role in fuelling economic growth.

Three main realms have been identified that contribute towards this MTS; (i) improving vehicle efficiency, (ii) implementing systemic improvements in road freight operations and logistics, and (iii) shifting to trucks that rely on alternative fuels. A combination of timely and effective policies centred on these three areas has the potential to reduce WTW GHG emissions by 60% relative to 2015 levels in the MTS, while current national pledges indicate an expected rise in emissions of 56% over this same period. Table 2.5 provides a summary of the key results from these two scenarios compared against a 2015 baseline.

Table 2.5: Activity, energy, and emissions summary for RTS and MTS

Metric	2015	2050 - RTS	2050 - MTS
Freight Activity (trillion tkm)	28	67	58
Energy Consumption (Final Energy - EJ)	36	53	27
Oil Consumption (Final Energy - EJ)/ (Share in Total Final Consumption)	35/97%	45/84%	12/44%
WTW GHG Emissions (Gt CO ₂ eq)	3.1	4.8	1.2

The reduced dependence on fossil fuels is created through three key enablers that present no-regret opportunities from an energy policy perspective, one for each category of potential improvements:

Adopting policies targeting vehicle efficiency, including fuel economy standards and differentiated taxes on vehicle purchase; the two policies complement each other: the former regulatory policy ensures that all new truck sales achieve minimum efficiency performance, and the latter fiscal measure favours the best performing models, pushing further improvements. For MFTs and HFTs taken together, the fuel use per kilometre of new vehicle registrations needs to be progressively reduced by 35%, relative to a 2015 baseline, by 2035. To achieve this, fuel economy standards for heavy-duty vehicles need to be broadened far beyond their current application in only four countries to cover all the HDV main vehicle markets. Once heavy-duty fuel economy policies are in place, their stringency needs to be successively raised, accounting for cost reductions delivered by technological progress.

Supporting widespread data collection and information sharing: Data gathering and information sharing are key prerequisites to realising some of the potential that underlies systemic improvements of freight logistics, including the sharing of assets and services. Policy makers should take a proactive role in supporting data collection and sharing platforms by promoting closer collaboration among all stakeholders, including government, citizen groups and corporate actors operating across the supply chain. Open data protocols that protect proprietary data while enabling supply chain collaborations can unlock potentially operational efficiency potential of large but uncertain magnitude.

Promoting the deployment of alternative fuels and the vehicles that use them: The use of alternative fuels requires different types of policy involvement, depending on the fuel in question (natural gas, biofuels, electricity or hydrogen) and the state of technological maturity. Their deployment typically requires support across four areas: RD&D, market uptake of alternative fuel vehicles, adequate access to charging or refuelling infrastructure and the availability of alternative fuels.

Chapter 3

Low Carbon Pathways for Light Commercial Vehicles in Ireland

Abstract

This chapter follows a similar theme to Chapter 2 by focusing on the energy and related CO₂ emissions associated with light commercial vehicles (LCV) in a more localised setting for an individual nation, Ireland. Transport is the most significant energy consuming sector in Ireland, accounting for 40% of final energy demand in 2013, with private cars and road freight contributing 51% and 25% to transport energy demand respectively. While a large literature body exists analysing private car energy use, there has been little published analysis on freight transport. This chapter develops a range of low carbon pathways for LCV transport in Ireland which align with an 80% CO₂ emissions reduction by 2050 (relative to 1990), using scenario analysis and a multi-model approach, which included i) the Irish TIMES energy systems model – a least cost optimisation model of the Irish energy system - and ii) an LCV stock model for Ireland – a sectoral simulation model of LCVs in Ireland. The introduction of energy efficiency measures and indigenous gaseous biofuels were found to be key elements in a technically feasible roadmap, which can meet the required CO₂ emissions reduction target.¹

¹ Chapter based on the published journal article: Mulholland, E., O Shea, R., Murphy, J. D., Ó Gallachoir, B. P., “Low Carbon Pathways for Light Goods Vehicles in Ireland”, *Research in Transportation Economics*, vol. 57, pp. 53 – 62, 2016

3.1 Introduction

Transport is the most energy intensive sector in Ireland, accounting for over 40% of total final energy consumption in 2013 (SEAI, 2014). Within this sector, on-road transport accounted for 67.5% of the total final energy consumption in the same year, with 43% attributable to private cars, 21% to road freight, and 3.5% to public transport (Dineen et al., 2014). However, a misalignment lies between the energy consumption of these modes and the focus of policy aimed at decarbonisation. For example, In the Irish National Mitigation Plan, which provides a list of potential long-term decarbonisation measures across the energy system, 6 of the 24 transport specific measures were targeted directly at promoting public transport, while only one explicitly mentions light commercial vehicles (LCVs) and only one mentions heavy good vehicles (HGVs) (DCCAE, 2017). This chapter aims to provide more clarity for policy makers in the area of freight, specifically with regards to LCVs, and identify policy measures with a potential capability of providing long-term decarbonisation.

The motivation for the drive towards decarbonisation-focused policy is strongly motivated by the increasing national interest on renewable penetration over the last decade, strongly driven by the Copenhagen Accord which established a political consensus on limiting a rise in mean global temperature to 2°C relative to the pre-industrial era, and further endorsed by the 21st Conference of Parties, held in Paris in 2015. The Inter-Governmental Panel on Climate Change (IPCC) fourth assessment report detailed the need for a global reduction in greenhouse gas (GHG) emissions of 50% by 2050 relative to 1990 in order to limit global temperature rise to 2°C (IPCC, 2007). Following this analysis, the European Commission advised that in meeting this target it is the responsibility of the countries which are members of the Organisation for Economic Co-operation and Development (OECD) to reduce GHG emissions to a level between 80% and 95% by 2050 relative to 1990 (European Parliament, 2011a).

This transition to a low carbon future will be onerous; the transport sector is currently heavily dependant on gasoline and diesel as sources of fuel, with consumption of liquid biofuels in Ireland amounting to little over 100 ktoe in 2013, representing 2.4% of total transport demand (SEAI, 2014). These biofuels represent a very large portion of Ireland's current renewable transport, with little contribution from renewable electricity (Dineen et al., 2014). These biofuels initially emerged from 2005 onwards following the introduction of the biofuels directive (European Parliament, 2003). Furthermore, the Biofuels Obligation Scheme (BOS) was introduced in Ireland in 2010, obliging suppliers of mineral oil to ensure that at least 4.166% (by volume) of motor fuels sold on the market

came from renewable sources.² This scheme represents Ireland’s main ambition of achieving a renewable energy share in transport of 10% by 2020, a target mandated by the European Union (EU) (European Parliament, 2009b). However, the blending of conventional biofuels with gasoline or diesel is restricted to 5% (CEN, 2008) and 7% (CEN, 2009) respectively, showing that Ireland faces significant difficulty in moving to a low carbon future for LCVs, which are almost entirely fuelled by diesel.

Ireland stands slightly above average amongst EU member states regarding renewable energy in transport, as shown in Figure 3.1 (Eurostat, 2017a). Ireland’s target is to achieve a 20% reduction of non-Emissions Trading Scheme (non-ETS) sector emissions by 2020, and in 2013 transport accounted for 19% of non-ETS emissions showing that there is significant potential to reduce non-ETS emissions through the decarbonisation of transport (EPA, 2015).

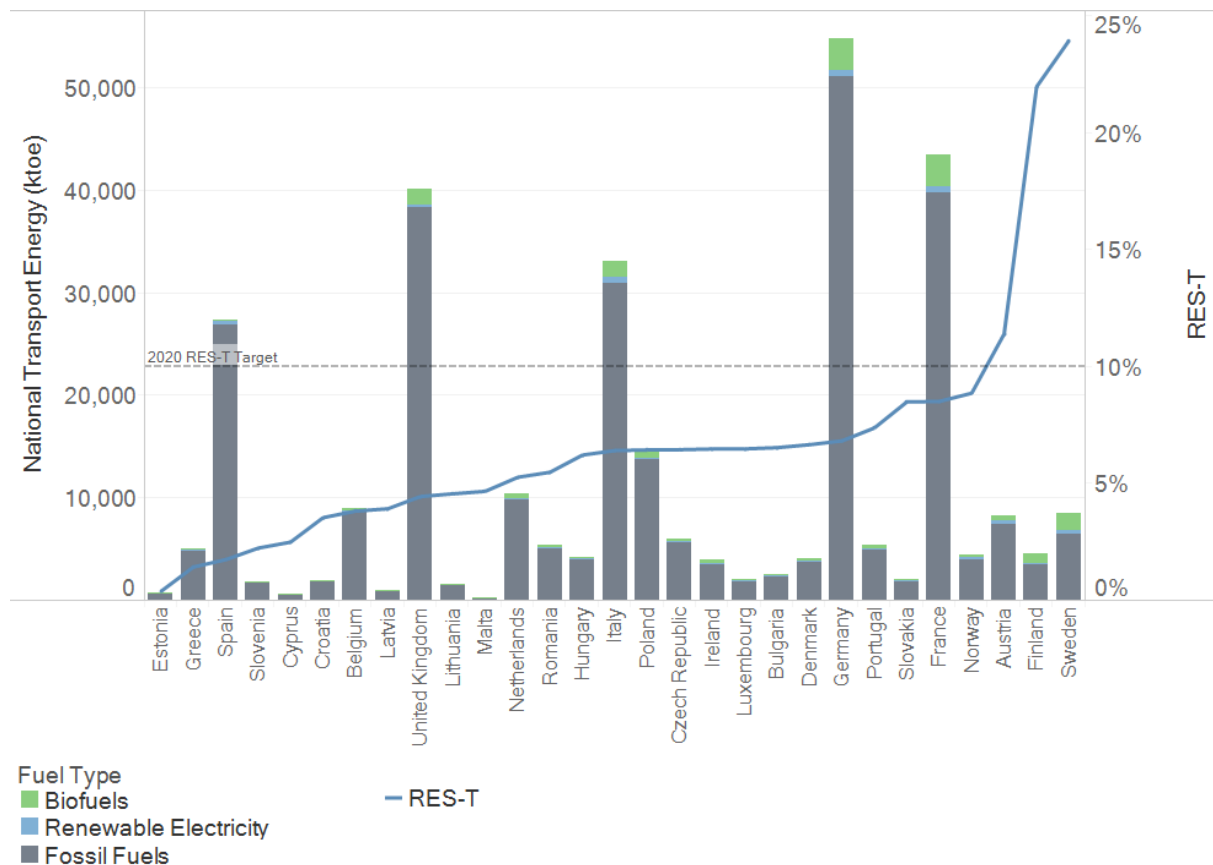


Figure 3.1: Share of renewable energy in transport in Europe in 2015

To date, energy models have been commonly used in mapping out low-carbon pathways in the transport sector (Chiodi et al., 2013a, Yang, 2013, McCollum et al., 2014). The focus of many

² As of the 1st of January, 2017, this figure was increased to 8.695%

transport specific energy models have been centred on creating projections of stock, energy, and low-carbon pathways to decarbonise on-road transport - (Daly and Ó Gallachóir, 2012, Siskos et al., 2015, Whyte et al., 2013, Yang, 2013). In general, modelling transport demand only becomes accurate with a sufficient level of data present. Considering the history of transport modelling in Ireland, projections of HGVs (Whyte et al., 2013) and the private car fleet (Daly and Ó Gallachóir, 2011b) have been possible through the use of extensive data provided by the Central Statistics Office (CSO) and National Car Test (NCT) respectively, dating back to 1995 for HGVs through the annual freight survey carried out by the CSO and dating back to 2000 for private cars when car testing became obligatory for all cars aged four years and older. In the past, little data has been available for LCVs in Ireland, alongside many other countries, creating difficulty in the formation of technical detailed transport models focused on this mode. However, annual mandatory testing came into effect in Ireland for LCVs in 2007, thus providing the data which allowed for an LCV stock model to be built within this chapter.

The definition of LCVs varies between countries. For the purpose of this chapter, an LCV is defined as a commercial vehicle with an unladen weight between 0 kg and 2,032 kg, in line with the vehicle testing standards as laid out by the Commercial Vehicle Road-Worthiness Test (CVRT). In Ireland LCVs consist predominantly of vans (73% of LCVs in 2013) as well as jeeps (14%), crew cabs (7%), pick-up trucks, estates, chassis cabs and open lorries (6%) and are fuelled almost completely by diesel (99.75% of LCVs) as of 2013 (DTTAS, 2015). This chapter identifies potential transitions to decarbonise LCVs in Ireland through an increase in the level of biofuels and improvements in fuel economy.

Two scenarios are assessed: an 80% reduction of CO₂ emissions in Ireland by 2050 relative to 1990, and the same scenario with the added constraint of no imported biofuels. The latter scenario is considered due to the high dependency of biofuels in the freight sector contrasted against the uncertainty of availability of imports of bio-energy in the future. These scenarios are run by the Irish TIMES model – a least-cost techno-economic optimisation energy systems model of Ireland – which indicates the least-cost pathway in freight (HGVs and LCVs combined) to contribute to this target. These results are then soft-linked with a techno-economic LCV stock model to highlight technology pathways and policy roadmaps which may be taken to reach these targets. The integration of these modelling methods allows first for a cost optimal scenario to be developed in Irish TIMES with the feasibility of the results tested by the LCV Stock Model which has a much more detailed representation of the stock and survival profiles of Irish LCVs. This stands in contrast to Chapter 2

which used a simulation modelling framework to determine low carbon opportunities within the freight sector, without any inclusion of optimisation modelling.

This chapter is structured as follows: Section 3.2 introduces the models used, giving a specific focus to the LCV stock model, and introducing the scenarios used to heavily reduce the dependence on fossil fuels in the LCV sector. Section 3.3 identifies the feasibility of decarbonizing the LCV sector and presents the technology and policy roadmaps which may allow a contribution from the LCV sector in meeting the targets laid out by the scenarios used. Section 3.4 highlights points of interest regarding the decarbonisation of LCVs and availability of biofuels. Section 3.5 concludes and highlights areas of further work along with limitations to the modelling techniques used.

3.2 Methodology

Two models are employed and soft-linked in this analysis: the Irish TIMES model and the LCV Stock Model. The Irish TIMES model is a linear optimization techno-economic model which uses a bottom-up approach to generate a least-cost solution for the energy system, subject to certain constraints. The LCV Stock Model is a techno-economic sectoral simulation model which uses a high level of technical detail to provide a more holistic view on the LCV sector than what Irish TIMES may offer. This allows for Irish TIMES to provide a cost-optimal scenario and for the entire energy system, and for the LCV Stock Model to analyse the feasibility of achieving the transport specific results outlined by Irish TIMES. This section describes the methodologies behind each model and how they are used in projecting a low carbon pathway for LCVs.

3.2.1 Irish TIMES Model

The Irish TIMES model is a linear optimisation model with an objective function to minimise total system cost subject to imposed constraints for the Irish energy system (Chiodi et al., 2013a, Chiodi et al., 2013b). The model uses mathematical equations to describe the relationships and interaction between the many technologies, drivers and commodities. It simultaneously solves for the least cost solution subject to emission constraints, resource potentials, technology costs, technology activity and capability to meet individual energy service demands across all sectors. When deciding between technologies, the model takes into account residual capacity (e.g. existing cars on the road), their fuel, and operational and maintenance costs. It then compares them against new technologies which could be introduced in place of those already existing, but in general these technologies have improved efficiencies and lower emissions. Generally, the model is run in the absence of policy constraints and then re-run with a constraint (e.g. maximum permitted level of CO₂ emissions). The

outputs include the costs, level of efficiency required, and fuel switching in each sector to achieve this constraint at least cost. A more detailed account of the model operation and input assumptions can be found in Appendix B.

3.2.2 LCV Stock Model

There are some notable pieces of work to date which have identified the importance of modelling LCV activity and energy use. In Browne et al. (2014), survey data from the UK and France is used (while stating the implications related to the lack of data in this sector) to highlight the patterns in van activity and identifies the opportunity for electric vehicles to reduce emissions. Similarly, the Commission for Integrated Transport (2010) highlights a growth in van activity of 40% in the UK over the time period 2000 to 2010 and criticises the lack of knowledge of data in this area.

In general, freight projections are driven by tonne kilometres (tkm), as is the case in Chapter 2, (Whyte et al., 2013) and (Kamakaté and Schipper, 2009), however the main complication with modelling LCVs arises due to the lack of data detailing how many trips are carried out which involve the actual transfer of goods e.g., an electrician may use a van to drive to a household and provide a service without any physical transfer of goods. This chapter is reliant on the data available, which is recorded in vehicle kilometres (vkm) by the CVRT rather than tkm, and so projections of vkm are used to drive this model. All variables are disaggregated by seven unladen weight bands (see Table 3.1) and are projected from the base year, 2013, to a time horizon of 2050.

3.2.2.1 Variable Projection

3.2.2.1.1 Mileage

Vehicle kilometres are projected using data from the CVRT which obliges all Irish LCVs to be tested annually. Gross national product (GNP) and fuel prices are used as drivers for vkm and are projected exogenously to 2050 by the Economic and Social Research Institute (ESRI) and the European Commission respectively (Bergin et al., 2013a, Capros et al., 2013). These projections are used in tandem with an income elasticity of demand (γ_I) and a fuel elasticity of demand (γ_{FP}). A mean long-run income elasticity of demand of 0.93 was chosen based on a review of traffic-related elasticities of demand using a combination of 150 published values from a range of international studies (Graham and Glaister, 2011). A fuel elasticity of demand (γ_F) of -0.1 is chosen from the National Road Authority (NRA) (NRA, 2013), inferring that a change in fuel price will have a minute effect on total LCV energy demand. Equation 3.1 describes the projection of total vehicle kilometres for a year 'Y'.

Equation 3.1 summarises this method of projection:

$$vkm^Y = vkm^{Y-1} * (1 + \Delta GNP^Y * \gamma I^{vkm}) * (1 + \Delta FP^Y * \gamma FP^{vkm}) \quad (3.1)$$

The average annual mileage per vehicle is linearly projected based on the 13 years of available data from the CVRT. An annual average reduction of 0.63% in the mileage of LCVs over this time period is used in the projection of vkm/year based on this historic data.

3.2.2.1.2 Specific Energy Consumption

At the time of writing, there were limited levels of data available regarding the specific energy consumption (SEC) of Irish LCVs. The Sustainable Energy Authority of Ireland (SEAI) create estimates of the SEC of LCVs by linking a database of the makes and models of LCVs licensed in Ireland (accessed from the Vehicle Registration Unit (VRU)) with the UK's Vehicle Certification Agency's database of official vehicle fuel consumption test results. However, fuel consumption of new LCVs has only been recorded in this database since 2011, creating a data gap for LCVs manufactured earlier than this year. The LCV stock model uses a portfolio of all vintages, and so to provide an accurate depiction of energy consumption in the base year, the model requires the SEC for LCVs of all ages. To address this gap, a Finnish study dedicated to unit emissions of traffic is used to estimate the SEC of LCVs by unladen weight (Mäkelä and Auvinen, 2007).

The study concludes that the energy consumption and emissions are *"to a certain extent linearly dependant on the mass of the vehicle"*. The SEC of LCVs for all seven unladen weight bands (shown in Table 3.1) are determined through both linear interpolation and extrapolation using unladen weight 'm' and the SEC from the goods carrying vehicles used in the study. This methodology is used for determining the SEC of vehicles in Ireland between 1988 and 2010. Table 3.1 shows the calculated SECs using Equation 3.2, where 'a', 'b', represent two unladen weight bands while 'x' represents an unladen weight band which falls between 'a' and 'b'.

$$SEC_x = SEC_a + \left(\frac{m_x - m_a}{m_b - m_a} \right) * (SEC_b - SEC_a) \quad (3.2)$$

Table 3.1: Historic specific energy consumption of LCVs

Unladen Weight Band (kg)/ Euro LCV Standard	Specific Energy Consumption (MJ/km)						
	0 - 610	611 - 813	814 - 1016	1017 - 1270	1271 - 1524	1525 - 1778	1779 - 2032
Euro 5 (>2009)	2.56	2.75	2.84	2.95	3.07	3.19	3.31
Euro 4 (2007 - 2008)	2.88	3.04	3.12	3.21	3.30	3.40	3.50
Euro 3 (2001 - 2006)	2.88	3.04	3.12	3.21	3.30	3.40	3.50
Euro 2 (1997 - 2000)	2.99	3.15	3.22	3.31	3.41	3.51	3.61
Euro 1 (1994 - 1996)	2.99	3.15	3.22	3.31	3.41	3.51	3.61
<1993	2.99	3.15	3.22	3.31	3.41	3.51	3.61

The deterioration of an LCV internal combustion engine (ICE) is accounted for by multiplying the SEC (in MJ/km) by a factor of 1.003^v , where v is the vintage of the LCV, and is assumed from Van den Brink and Van Wee (2001). This equates to a progressive reduction in the fuel economy of the vehicle in a year-on-year basis.

The SEC of the bio-methane fuelled LCV stock is taken as the average performance from four of the six dual fuel vans (petrol and gas) – chosen to get an accurate representation of average van size in Ireland - which had an unladen weight of approximately 1,500 kg, used by Gas Networks Ireland (GNI). Compared to diesel LCVs, the dual fuel vans have a higher rated SEC; a diesel LCV in 2050 has an average SEC of 1.15 MJ/km while CNG LCVs have a SEC of 1.57 MJ/km. No on-road factor is taken into account (the difference between actual and test emissions) for diesel LCVs while ‘real-world’ data is used for bio-methane LCVs.

3.2.2.1.3 Stock

LCV stock is disaggregated and projected by the seven unladen weight bands, as shown in Figure 3.2. The largest 4 of these bands constituted 96% of the total stock, with less than 1,900 LCVs having an unladen weight of less than 813 kg. These stock figures may further be disaggregated into vintages up to 20 years old, shown on the right side of Figure 3.2.

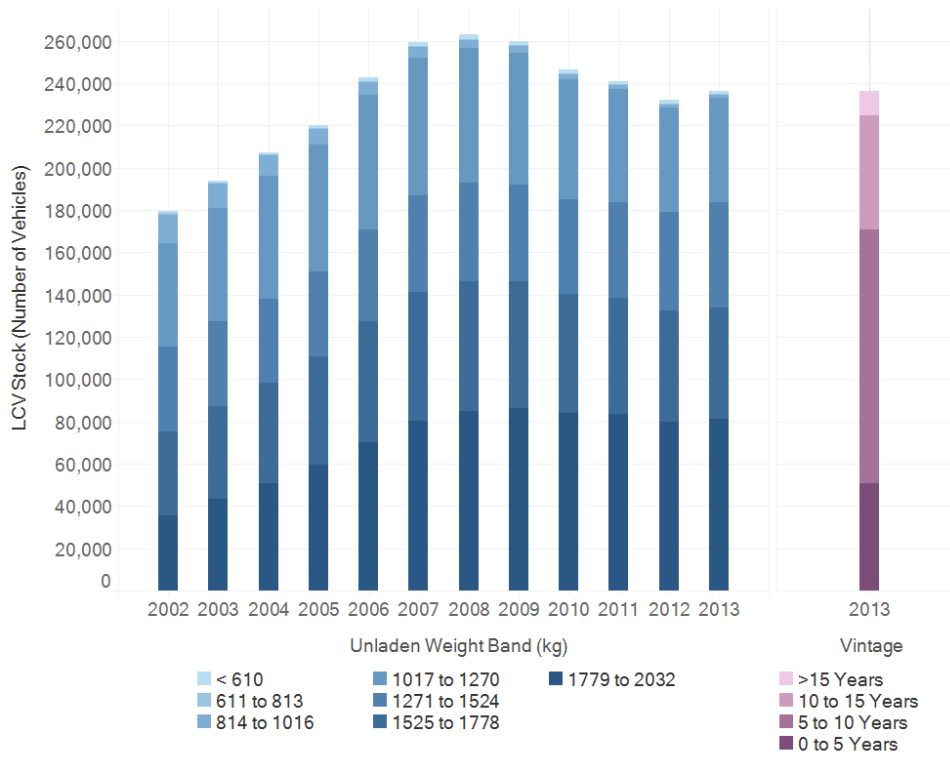


Figure 3.2: Historic stock profile of LCVs. Source: (DTTAS, 2015)

The detailed level of data pertaining to stock is used to create survival profiles for the various unladen weight bands of LCVs, using the same methodology carried out by Daly and Ó Gallachóir (2011a) for private cars. Survival profiles are based on year of registration, rather than year of manufacture, to account for the importation of LCVs into Ireland. A year-on-year survival probability is calculated using Equation 3.3, which describes the survival rate as the probability of one LCV of vintage 'v' in an unladen weight band 'UWB' surviving to a vintage 'v+1'.

$$Survival Rate_v^{UWB} = Average \left(\frac{(Stock_v^{UWB} - Stock_{v-1}^{UWB})}{Stock_v^{UWB}} \right) * (1 + Survival Rate_{v-1}^{UWB}) \quad (3.3)$$

The stock for every LCV disaggregated by unladen weight band and vintage 'v' for every year 'y' is calculated using Equation 3.4. The calculated survival profiles show a small number of imports of LCVs in the unladen weight band 611 to 813 kg, represented by a probability of survival greater than 100. Smaller weight bands were seen to have a lower probability of survival for the same vintage relative to its heavier counterpart (see Figure 3.3).

$$Stock_{v,y}^{UWB} = Stock_{0,y-v}^{UWB} * Survival Rate_v^{UWB} \quad (3.4)$$

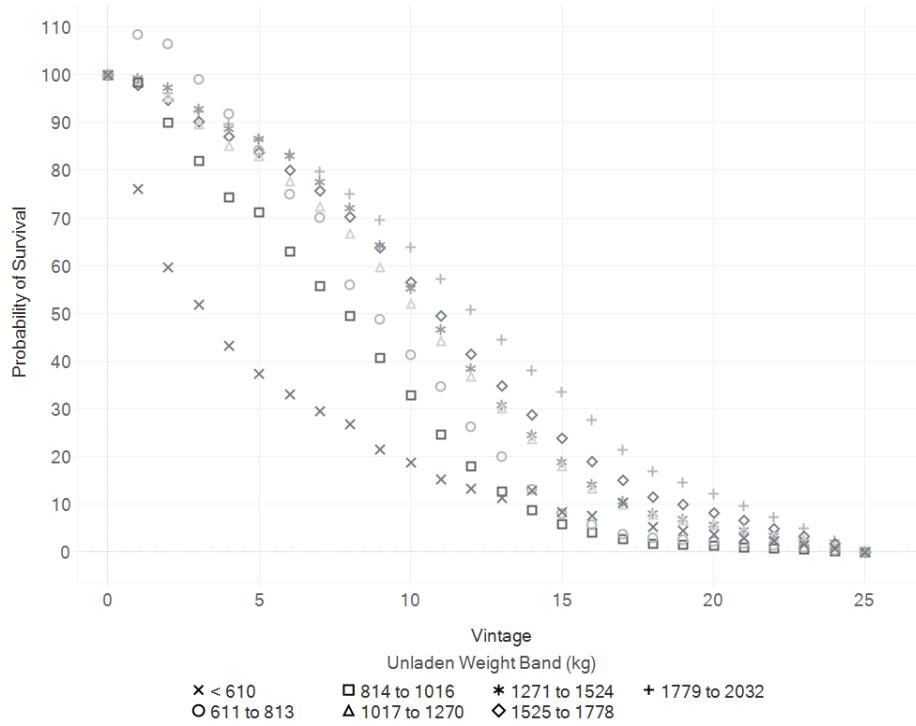


Figure 3.3: Survival profiles of LCVs in Ireland

Total emissions in the LCV sector are calculated as the product of the stock, mileage, and SEC of each disaggregated band, i.e, vintage and unladen weight, multiplied by an emissions factor, mimicking the ASIF methodology initially proposed by Schipper et al. (2000). An emissions factor of 88.8 gCO₂/MJ for diesel (well-to-wheel (WTW) analysis) is taken from Korres et al. (2010) while the level of biofuel blending is taken from (Dineen et al., 2014). As mentioned in Section 3.1, there is a maximum blend on the blending of biofuels with petrol and diesel - I.S. EN 590 and ASTM D975 state a maximum of 7% of bio-diesel by volume is allowable in conventional ICEs. Therefore, this chapter uses an assumption that a blending of 5% of bio-diesel with diesel is achieved by 2020 and held constant to 2050.

$$LGV\ Emissions_f = Emissions\ Factor_f * \left(\sum Stock_v^{ULW} * Mileage_v^{ULW} * SEC_v^{ULW} \right) \quad (3.5)$$

3.3 Low Carbon Scenarios

3.3.1 Irish TIMES Scenarios

Two scenarios are explored using the Irish TIMES model. The first stays in keeping with the recommendations laid down by the EU for OECD countries from the Copenhagen Accord which achieves an 80% reduction in CO₂ emissions by 2050 relative to 1990 (*CO₂-80 scenario*), describing the level of effort required by the freight sector in order to achieve the overarching constraint. The

second scenario carries out the same analysis as the CO₂-80 scenario with the added constraint of a restriction on the importation of any biofuels. The purpose of this scenario is to prevent any external dependency on imports of biomass in the future and determine what the next cheapest alternative is (*CO₂-80 NoBioImp Scenario*).

3.3.1.2 Irish TIMES Indigenous Biofuel Resource

Biofuels have been identified as a low carbon solution for on-road freight vehicles (Drosg et al., 2014, IEA, 2009, IEA, 2010). For this reason, a focus in this chapter is given to the biofuels available for freight energy demand. The Irish TIMES model takes an input of total potential bio-energy from domestic and foreign sources. The model uses this information to calculate the contribution which biofuels may have in a low carbon scenario. Table 3.2 identifies the current potential resource in Ireland for biofuel by 2050, as used by the Irish TIMES model (Chiodi et al., 2013b). The largest potential fuel output from indigenous biofuel for transport is bio-methane sourced from biogas with a total energy potential of 1,272.42 ktoe.

Table 3.2: Projected Irish domestic bioenergy resource to 2050. Source: (Chiodi et al., 2013b)

Projected Irish Domestic Bioenergy Resource in 2050		
Feedstock	Fuel Source	Energy Potential (ktoe)
Dry Agricultural Waste Potential	Woody Biomass	187.97
Wheat for Ethanol Production	Bio-ethanol	45.26
Miscanthus Crops for Biomass	Woody Biomass	352.51
Willow Crops for Biomass	Woody Biomass	316.14
Forestry Residues	Woody Biomass	326.15
Landfill Gas	Biogas	57.25
Grass Silage	Biogas	1136.21
Municipal Waste Production	Solid Fuel	1031.40
Rape Seed Production	Biodiesel (or Bio-glycerol)	2.35
OSR for Biodiesel Production	Biodiesel (or Bio-glycerol)	133.36
Wet Industrial Waste	Biogas	78.96
Wood Processing Residues	Woody Biomass	137.00

Biogas produced from the anaerobic digestion (AD) of biological material typically consists of 55-70% methane, 30-40% carbon dioxide, and <5% trace gases such as nitrogen, oxygen, and hydrogen sulphide (Browne et al., 2011). Biogas can be upgraded to bio-methane by removal of the carbon dioxide component of the gas, along with the trace gases such as hydrogen sulphide. The resulting upgraded bio-methane contains approximately 97% methane which can then be injected into the natural gas network or into gas cylinders to facilitate its transportation to end users either through the gas network or via road haulage.

Bio-methane production facilities can utilise a number of differing feedstock. Previously published work by Browne et al. (2011), Singh et al. (2010), and Wall et al. (2013) has analysed the resource associated with a range of feedstock in Ireland including grass silage, animal slurries, and the organic fraction of municipal solid waste. The tonnage of feedstock accepted at bio-methane-to-grid facilities in the UK ranged from 16,000t/year to 300,000t/year depending on the feedstock utilised. The average tonnage accepted by plants was 46,000 t/year however a large degree of variation was evident (standard deviation in excess of 50,000t/year (NNFCC, 2015)). This is calculated using the average accepted annual tonnage of 30 bio-methane-to-grid facilities in the UK as of October 2015. This analysis proposes for facilities to accept 50,000 t/year of feedstock to reflect previous work carried out for Ireland (Browne et al., 2011, Singh et al., 2010) and current data from UK plants. Wet wastes (comprising primarily of cattle and pig slurries) and grass silage are the feedstock analysed in this section, which will be co-digested in plants as these are the largest resources which can be utilised for the production of bio-methane that are currently recognised in the Irish TIMES model. The co-digestion of grass silage and slurries has been shown to result in improved digester performance in previous work (Wall et al., 2014) and is common practice in numerous AD systems. In the UK for example, 7 of the 30 bio-methane-to-grid plants co-digest animal slurries along with crop and/or grass silages (NNFCC, 2015).

It is assumed in this analysis that the entire resource associated with cattle slurries and pig slurries is utilised in each of the scenarios investigated, with the remaining bio-methane requirement coming from grass silage. The quantities of cattle slurry and pig slurry available in the TIMES model are sourced from Clancy et al. (2012), the energy resource of cattle slurry and pig slurry are 11.77 ktoe (0.49 PJ) and 54.73 ktoe (2.29 PJ) respectively. The volatile solids component of cattle slurry, pig slurry and grass silage (the portion of matter than can be converted to biogas in AD) along with the specific methane yield per unit mass of volatile solids may be noted in Table 3.3. These values were used to determine the methane yield per wet tonne of cattle slurry, pig slurry and grass silage (Table 3.3). The energy content of methane used in this work is 37.78 MJ/Nm³ (Singh et al., 2010), this allows for the energy production per wet tonne of slurry and grass to be determined.

Table 3.3: Feedstock properties

Feedstock	Volatile Solids Fraction (% wwt*)	Methane Yield (m ³ CH ₄ /tVS)	Methane Yield (m ³ CH ₄ /t wwt*)	Energy Yield (MJ/t wwt*)	Source
Cattle Slurry	6.2	143	8.9	335	(Wall et al., 2014)
Pig Slurry	2.6	292	7.6	286.8	(Xie, 2012), (Angelidaki and Ellegaard, 2003), (Asam et al., 2011), (Thygesen et al., 2014), and (Xie et al., 2011)
Grass Silage	26.8	414	111	4191.8	(Wall et al., 2014)

*t wwt: Tonne wet weight

3.3.2 LCV Stock Model Scenarios

Three scenarios are analysed to quantify the emissions reductions associated with the measures taken in all scenarios. First, a business as usual (BaU) scenario is developed which assumes no improvement in the energy efficiency of LCVs from now to 2050 with no switch over to renewable fuel vehicles. The BaU marks a baseline for all other scenarios as to what may happen in the absence of any new policies.

The second scenario quantifies the potential emissions reduction from focusing on the efficiency improvements of LCVs, with no penetration of renewable vehicles. A focus is placed on three individual efficiency measures. The first limits the average specific emissions of all new LCVs to 147 gCO₂/km, as mandated by The European Parliament and the Council of the European Union in Regulation EU No. 510/2011 (European Parliament, 2011b). The second simulates the switch to more efficient vehicles following the simulation of a policy in 2021 which bases LCV tax on emissions, rather than unladen weight as is the case today. This simulation uses the same percentage change in the efficiency of the private car fleet for the five years following the change in taxation from engine size to specific emissions in 2008 (3.8% improvement per year), which saw a drop in the emissions of the new car fleet (Rogan et al., 2011). Finally, an improvement in the fuel economy of LCVs out to 2050 is assumed based on the IEA's Energy Technology Perspectives report which identifies a potential 47% improvement in the efficiency of light-duty vehicles relative to a baseline gasoline vehicle (IEA, 2008).

The final scenario combines the improved efficiency scenario with the penetration of renewable LCVs – compressed natural gas (CNG) LCVs fuelled by bio-methane. To simulate this technology, data from the 6 gasoline and gas fuelled vans owned by GNI is used. The purpose of this scenario is to assess the feasibility of the penetration rates of biofuels in freight in the TIMES CO₂-80 and TIMES CO₂-80 NoBioImp scenario described previously. A summary of these scenarios are presented in Table 3.4.

Table 3.4: Scenario summary

Scenario	LCV Stock Model	TIMES Model
CO₂-80	-	80% reduction in CO ₂ relative to 1990
CO₂-80 NoBioImp	-	As above + no importation of biofuel
BaU	Baseline	-
Improved Efficiency	147 gCO ₂ by 2020 Switch of carbon tax bands in 2021 47% improvement in efficiency by 2050	-
Improved Efficiency + Renewable Vehicles	As above + renewable vehicle penetration to match TIMES scenario results	-

3.3 Results

The results section is split as follows; firstly, a comparative overview of the results from the CO₂-80 and CO₂-80 NoBioImp scenarios is presented in section 3.3.1, and secondly, policy roadmaps are presented from the LCV Stock Model based off the Irish TIMES scenario results in section 3.3.2, which may allow for the high-level penetration of bio-methane fuelled LCVs for the freight sector. Both of these analyses suggest that a high demand of biofuels will be required to decarbonise the LCV sector, and so section 3.3.3 discusses the infrastructure and source of feedstocks to satisfy this demand.

3.3.1 Irish TIMES Model

The transport sector experiences a drastic decarbonisation in the CO₂-80 scenario, with an 88% reduction in CO₂ emissions between 2010 and 2050. In contributing to this emissions reduction, a range of renewable technologies are employed by the model in the freight sector. Under the CO₂-80 scenario, there is a total energy demand of 1821 ktoe for all of freight (HGVs and LCVs). This consists of 318 ktoe of bio-methane and 240 ktoe of diesel, along with a total energy demand of 1263 ktoe

from a combination of bio-diesel, bio-dimethyl ether (Bio-DME), ethanol and gasoline. This scenario is heavily dependent on exogenous sources of bio-energy for freight with imports of 3,555 ktoe compared to indigenous production of biofuel and biomass of 1,757 ktoe in 2050.

The CO₂-80 NoBioImp scenario restricts the importation of any biofuels or biomass imports in Ireland, which reduces the level of biofuels in freight by 40% relative to the CO₂-80 scenario and uses hydrogen fuel cell vehicles as a substitute due to the limitation on biofuel and biomass imports, with near to no diesel being used as a fuel source in freight.

An assumption is made in the latter scenario that close to all LCVs will be powered by bio-methane while HGVs use a combination of hydrogen fuel cells and bio-methane as a fuel source. The fuel mix of freight (HGVs and LCVs) with corresponding emissions intensity is shown in Figure 3.4.

In the Irish TIMES model, freight is aggregated into LCVs and HGVs. Therefore, in recreating these scenarios in the LCV Stock Model, it is assumed that all the bio-methane in the CO₂-80 scenario fuels LCVs along with some diesel, while in the CO₂-80 NoBioImp scenario close to all LCVs are fuelled by bio-methane.

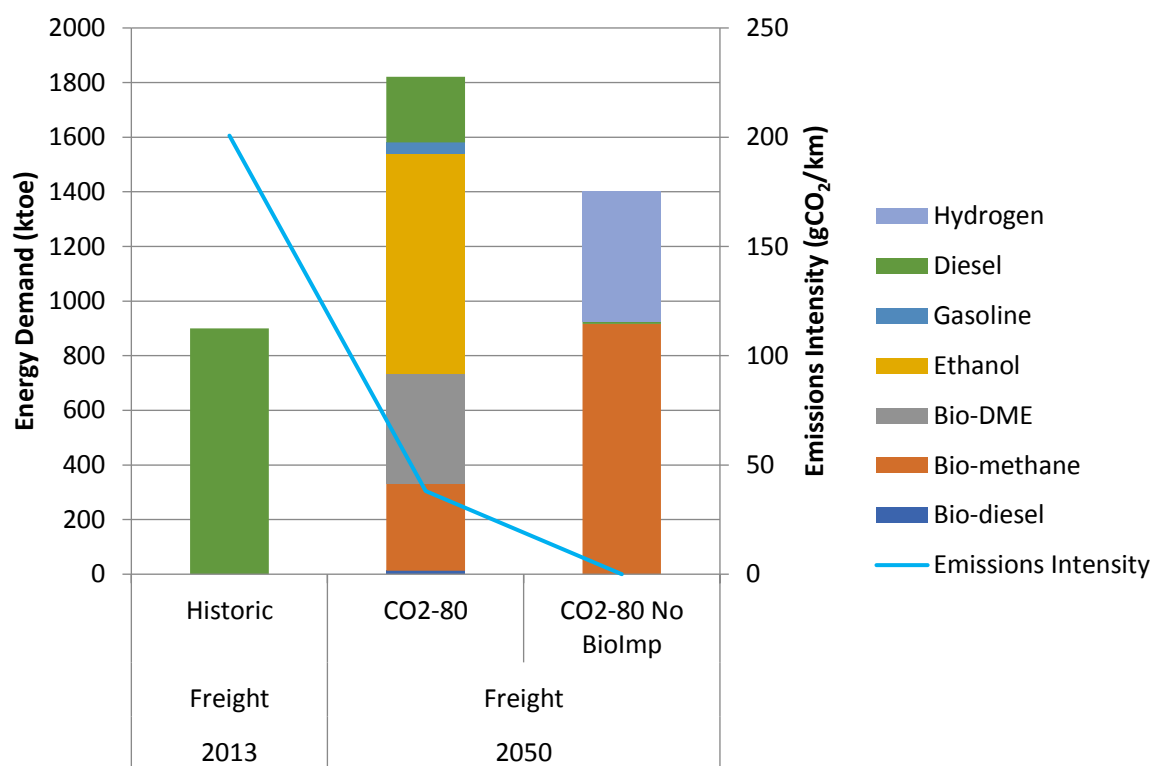


Figure 3.4: Final energy demand and emissions intensity of road freight by fuel in Irish TIMES

3.3.2 LCV Stock Model

The technology roadmaps from the Irish TIMES scenarios are tested in the LCV Stock Model to create policy roadmaps to 2050. The scenarios created allow for an insight into policy measures in Ireland, which may contribute towards a low carbon LCV sector. Three scenarios are used for this purpose: BaU, Improved Efficiency, and Improved Efficiency with Renewable Vehicles.

The BaU is intended to provide a baseline against which all other scenarios are compared. Under this scenario, LCV stock experiences a 36% increase by 2050 relative to 2013 which satisfies the total energy services demand of 8,357 million vkm – calculated using GNP as a driver – with an average of 25,925 vkm/LCV/year. The SEC of new LCVs is held constant at the 2013 values with a weighted average of 2.16 MJ/km. This is lower than the current average SEC of the LCV fleet of 3.37 MJ/km allowing for an overall improvement in the average fuel economy of LCVs as older inefficient LCVs are being replaced by more efficient vehicles. This results in an initial dip in the short-term LCV related emissions in Ireland until 2025, and increasing by 12.06% in 2050 relative to the base year.

The Improved Efficiency scenario focuses on the effect of a number of individual policy measures towards the improvement of energy efficiency of new LCVs and the corresponding reduction in fleet emissions. Meeting the 147 gCO₂/km target for new LCVs by 2020 as laid out by EU No. 510/2011 has only a slight reduction in emissions (3% relative to the BaU scenario) due to the nature of the short time span. This is a result of the small number of new LCVs entering the transport fleet between now and 2020 relative to the total LCV fleet, resulting in a slight impact on the level of emissions in the short term. However, this has a sufficient impact in the long-term due to the continuous introduction of new LCVs every year. Using the change in taxation policy in private cars as an example (a change from being based on the engine size to specific emissions in 2008 which resulted in an improvement in the fuel economy of new private cars in Ireland), a similar policy is simulated in LCVs. A change in the policy for taxation of LCVs from unladen weight to specific emissions resulted in a 13% reduction by 2025, relative to the BaU, following an improvement in fuel economy, assuming that LCVs will experience the same improvement in fuel economy as private cars. Finally, the highest potential of fuel economy from engine and non-engine components identified by the IEA by 2050 (47% improvement in the efficiency of light-duty vehicles relative to a baseline gasoline vehicle) contributes to a total reduction in emissions of 41% by 2050 relative to the BaU. This scenario highlights the total potential of reducing emissions by focusing solely on energy efficiency improvements of conventional ICE engines without considering the adoption of alternative or renewable fuel.

The final scenario considers the level of effort required to decarbonise LCVs according to the Irish TIMES scenarios through the penetration of bio-methane fuelled LCVs. This decarbonisation is modelled using an initial introduction of LCVs fuelled solely by bio-methane – in reality there will be an introduction of CNG LCVs and a gradual penetration of bio-methane into the gas grid while this analysis considers only the end goal of providing enough bio-methane to fuel the number of LCVs as laid out by the Irish TIMES model by 2050. At present, bio-methane has been identified to have the potential to satisfy 30% of Ireland’s gas demand by 2030, and a target has been proposed by GNI of 20% renewable natural gas on the gas network by 2030 (Gas Networks Ireland, 2015). The percentage level of sales of ICEs and bio-methane fuelled LCVs is varied in the LCV Stock Model to simulate the stock levels as laid out by the CO₂-80 and CO₂-80 NoBioImp scenarios. To achieve an 85% penetration of bio-methane in freight by 2050, CNGs require an annual increase of 5% share of all LCV sales from 2026 onwards, with 100% of all LCV sales from 2045 onwards being CNGs. In an extreme scenario where a 99% CNG penetration rate is required, a much faster increase in CNG sales is necessary. This scenario requires a linear increase from 2026 to 2030 in the rate of CNG LCV sales up to 100% and then held constant out to 2050. Figure 3.5 summarises the emissions reduction potential of these scenarios.

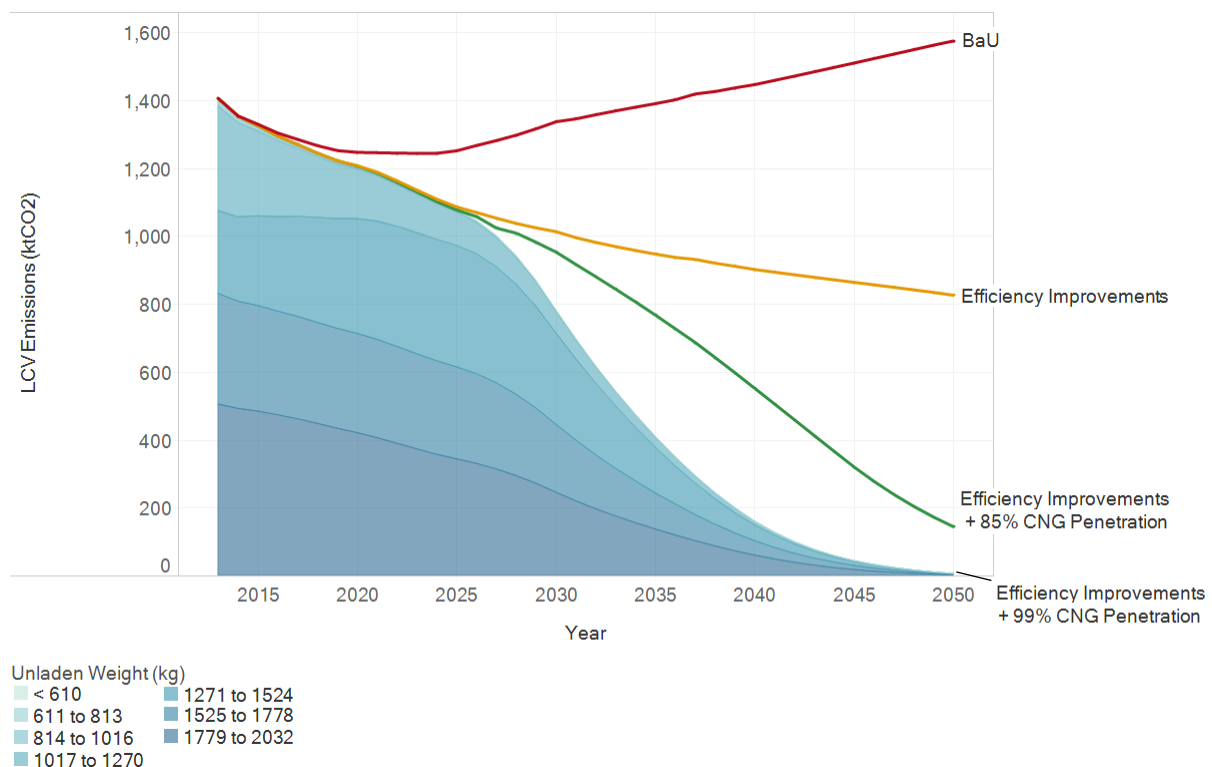


Figure 3.5: Potential emissions reduction from efficiency improvements in LCVs

Replicating the CO₂-80 scenario in the LCV Stock Model resulted in a final energy consumption of 307 ktoe from bio-methane fuelled LCVs. This is comparable to the Irish TIMES model which calculates a total bio-methane demand of 318 ktoe in 2050. In replicating the CO₂-80 NoBioImp scenario (increasing the penetration rate of bio-methane fuelled LCVs from 85% to 99% by 2050), the total bio-methane demand reaches 363 ktoe. The calculated emissions from LCVs in 2013 were 1,407 ktCO₂ while the Improved Efficiency scenario had 827 ktCO₂ emissions (41% reduction relative to 2013), an 85% penetration of bio-methane fuelled LCVs has corresponding emissions of 145 ktCO₂ by 2050 (89.7% reduction) and a 99% penetration has emissions of just over 6 ktCO₂ (99.6% reduction).

3.3.3 Bio-methane Infrastructure Requirement - 2050

3.3.3.1 CO₂-80 Scenario

The total consumption of bio-methane in the CO₂-80 scenario is 12.85 PJ, this is assumed to consist of 0.49 PJ from cattle slurry, 2.29 PJ from pig slurry, and 10.07 PJ from grass silage. Table 3.5 shows the tonnage of each feedstock as well as the mass share of each feedstock required to produce this amount of energy. It is calculated as the required energy quantity divided by the energy yield per tonne of feedstock.

Table 3.5: Breakdown of tonnage contribution to AD plants

Feedstock	Energy Quantity Required (PJ/year)	Mtonnes wwt/year	Mass Share of Feedstock (%)
Cattle Slurry	0.49	1.47	12.4
Pig Slurry	2.29	7.99	67.35
Grass silage	10.07	2.4	20.25

Applying the overall mass shares of each feedstock type to the proposed 50,003 t/year scale bio-methane production facilities results in the facility accepting; 33,676 t/year of pig slurry, 6,199 t/year of cattle slurry, and 10,126 t/year of grass silage, with an annual gross energy output of 54.18 TJ. A detailed breakdown of the results for the 50,000 t/year digester can be seen in the Table 3.6 for the CO₂-80 scenario.

Table 3.6: Energy output by feedstock

Theoretical 50,000 t/year Grass and Slurry Digester	Tonnage (tww/year)	Energy Production (TJ/year)
Annual Pig slurry	33,678	9.66
Annual Cattle Slurry	6,200	2.08
Annual Grass	10,125	42.44
Total	50,003	54.18

The total number of AD plants required in the CO₂-80 scenario is 237 in order to meet the required bio-methane energy consumption of LCVs.

3.3.3.2 CO₂-80 NoBioImp Scenario

The consumption of bio-methane by LCVs in the CO₂-80 NoBioImp scenario of 15.20 PJ would require 0.49 PJ from cattle slurry, 2.29 PJ from pig slurry, with the remaining 12.41 PJ being sourced from grass silage. Applying the same methodology as the previous section, the total number of plants, each processing 50,000 t/year of feedstock, comprised of 32,159 t/year pig slurry, 5,920 t/year cattle slurry, and 11,922 t/year grass silage, with an annual gross energy output of 61.18 TJ. The total number of the above AD plants required in the CO₂-80 NoBioImp scenario would be 248 in order to ensure that the demand for bio-methane from LCVs is satisfied.

3.4 Discussion

The main benefit of bio-methane fuelled LCVs compared to diesel is the mitigation of GHG emissions. A study published in 2010 compares the life cycle emissions of diesel to the production of grass bio-methane in Ireland (Korres et al., 2010). The study found that diesel has 21.5% more GHG emissions compared to grass bio-methane on a well-to-wheel (diesel) or field-to-wheel (grass bio-methane) basis (88.8 gCO₂eq/MJ for diesel and 69.74 gCO₂eq/MJ for grass bio-methane). A number of measures are identified to reduce this value to 40.66 gCO₂eq/MJ through: decarbonisation of the electricity provided to the digester, modification of the digester's heating configuration, and alteration of bio-methane fuelled vehicle operations. Complementary to this, grasslands sequester CO₂ through photosynthesis and emit it through respiration – allowing grass silage to be considered as either a sink or source of GHG emissions. A second Irish study calculated the total amount of emissions sequestered by grass to be equivalent to 7.33 tCO₂eq/ha/year (Kiely et al., 2009). Assuming a yield of 99.2 GJ/ha/year for grass silage (Korres et al., 2010), a total amount of 73.9 gCO₂eq/MJ is sequestered. Comparing this to the initial value of 40.66 gCO₂eq/MJ, grass silage has a negative CO₂ value of -33.24 gCO₂eq/MJ (or -4.16 gCO₂eq/MJ excluding measures), due to the storage of GHG emissions in the soils via its roots. However, in order to provide a conservative perspective, this analysis has taken grass silage to be carbon neutral.

Under the CO₂-80 scenario, a total of 237 facilities would be required in 2050 in order to meet the bio-methane requirement of LCVs, this would require the construction of approximately 7 plants per year if construction commenced in 2015. The average number of bio-methane to grid facilities built

in the UK between 2009-2015 was 5 per year, with 15 facilities completed in 2014 alone (NNFCC, 2015). As such, the construction of 5 such plants per year is not beyond the realms of possibility. The scale of the proposed plants in terms of electrical capacity is approximately 0.65 MW_e (assuming a conservative electrical efficiency of 38% and 8760 hours of operation per year (Clarke Energy, 2013)), the average electrical capacity of biogas plants which produce electricity in the UK is approximately 0.9 MW_e from a total of 217 plants (NNFCC, 2015) as such the scale of the proposed plants is within reasonable bounds. It should be noted for comparison that Germany has in excess of 10,000 facilities while Austria (with a population closer to Ireland) has ca. 4,000 (Persson and Baxter, 2014).

The total number of facilities required under the CO₂-80 NoBioImp scenario would be 248, which would again require approximately 7 plants to be built per year out to 2050 if construction commenced in 2015. The equivalent electrical capacity of the proposed 50,000 t/year bio-methane facilities in this instance is approximately 0.74 MW_e, once again this is a reasonable size when compared to the scale of existing CHP facilities in the UK. The number of plants producing bio-methane for grid injection in 2050 in the CO₂-80 NoBioImp scenario is approximately double the number of current bio-methane to grid plants in Germany which has 151 biogas upgrading plants as of 2014 (Linke, 2014); with two injection plants in existence as early as 2006 (Weiland, 2010). The average number of bio-methane to grid plants completed per year in Germany from 2011-2013 was approximately 32, this is greater than the required completion rate for the proposed 50,000 t/year bio-methane to grid plants analysed in this report highlighting the potential realism of this scenario. The rapid development of the anaerobic digestion industry was linked to favourable financial incentives made available to plant developers and highlights the potential for expansion of this industry if favourable incentives are in place. Recent reductions in the number of available incentives in Germany have resulted in a reduction in the roll out of new bio-methane plants (German Biogas Association, 2015) however, rapid expansion did occur when conditions were favourable.

An important point to note regarding this analysis is that the energy production per plant is the gross energy output of the plant, it does not take into account any inhouse consumption of the biogas or bio-methane which is produced. The rationale behind this assumption is that the inhouse requirement of electricity and heat can be met by purchasing electricity and other fuels such as wood biomass for heat production. The produced bio-methane is seen as too valuable a resource to use at the facility to satisfy parasitic energy demand (Browne et al., 2011).

3.5 Conclusion

A complete decarbonisation of the LCV sector in Ireland, which would contribute towards an 80% reduction in CO₂ by 2050 relative to 1990, is technically feasible through the combination of efficiency improvements and the use of biofuels. An overall 41% reduction in CO₂ emissions relative to a BaU is possible through improvements in the fuel economy of LCVs. To help contribute to emissions reduction in the short term, a change in the policy of taxation for LCVs from unladen weight to specific emissions would improve the fuel economy of new LCVs by 13%, relative to the baseline, if the same market response is mimicked in the LCV sector as the private car sector.

A penetration rate of 85% bio-methane fuelled LCVs by 2050 will contribute towards an 80% CO₂ emissions reduction by 2050, while a 99% penetration would be required if Ireland was to source all biofuels indigenously due to the lack of availability of ethanol and bio-DME locally. This is achievable through linear increase in percentage share of CNG LCVs from 0% in 2025 to 100% in 2045 for an 85% penetration level and an increase from 0% in 2025 to 100% in 2030 for a 99% penetration. In reality, a linear penetration rate is unlikely to happen and it would be more common to experience an 'S' curve – a slow take off of the technology following its introduction to the market and a faster up-take following the understanding and acceptance of the technology. In terms of energy performance, 'real world' CNG LCVs operate less efficiently than the test values from diesel LCVs. The lack of data regarding an on-road factor of diesel LCVs in this study suggests that diesel fuelled LCVs are operating more efficiently than would be expected in reality, while bio-methane LCVs are represented more accurately in the LCV Stock Model. There are considerably less emissions from LCVs fuelled by bio-methane compared to diesel. Replicating the Irish TIMES scenarios, there is the potential for between 1,262 ktCO₂ – 1,400 ktCO₂ reduction in CO₂ emission relative to the BaU (89.7% - 99.6%) by 2050 in the LCV sector, neglecting the emissions associated with the process of converting a feedstock to bio-methane.

The approach adopted in this chapter has expanded on that of Chapter 2 by including an optimisation model to a simulation techno-economic model, although the lack of inclusion of socio-economic measures has created certain limitations. For example, drivers of LCVs may be reluctant to invest in new vehicle technologies, such as compressed natural gas, and a multinomial logit choice model could be created using inputs of stated preference surveys to provide a more heterogeneous outlook on the LCV when modelling this sector.

Chapter 4

From Technology Pathways to Policy Roadmaps to Enabling Measures – A Multi-Model Approach

Abstract

Integrating a range of complementary energy models is becoming an increasingly common method of informing low carbon energy pathways at both national and global levels. Multi-modelling approaches facilitate improved understanding of the detailed *technology pathways* required to meet decarbonisation targets; however, to-date there has been limited attention on the *policy roadmaps* and *enabling measures* that might achieve these decarbonisation targets. This chapter addresses this gap by developing a multi-model approach using an energy systems *optimisation* model, a sectoral *simulation* model together with scrutiny of individual policy *measures* to explore decarbonisation of the private car sector in the Irish transport system commensurate with an 80% reduction in national carbon emissions by 2050. The results comprise a cost optimal technology pathway for private cars in a future energy system constrained by a maximum level of carbon emissions, a policy roadmap identifying annual changes in energy efficiency, renewable energy and electrification, and a suite of enabling measures including changes to vehicle registration tax, a biofuel obligation on suppliers and a suite of measure to increase the share of electric vehicles in the fleet. The level of confidence in the different enabling measures to achieve the policy goals is compared and discussed.¹

¹ Chapter based on the published journal article: Mulholland, E., Rogan, F., & Ó Gallachoir, B. P., "From technology pathways to policy roadmaps to enabling measures – a multi-model approach", *Energy*, vol. 138, pp. 1030 - 1041, 2017

4.1 Introduction

The recent focus on long-term global greenhouse gas emission (GHG) mitigation has led to the production of a wide array of energy and emission specific models with varying levels of sectoral and geographic focus. On the one hand, optimisation models are beneficial in determining a *technology pathway*, adept at depicting what technological changes are needed in an energy system subject to a constraint, usually GHG emissions, although with little or no indication of the required policy measures, e.g., the European Commission’s ‘Energy Roadmap to 2050’ (European Parliament, 2011a) and the International Energy Agency’s (IEA) ‘Energy Technology Perspectives’ (ETP) (IEA, 2016d). On the other hand, simulation models can effectively determine a *policy roadmap* which describe the policy steps and interim targets for emissions mitigation, although not necessarily with a focus on optimising around a certain scenario, e.g., the IEA’s World Energy Outlook (WEO) (IEA, 2016b) and the Irish ‘National Renewable Energy Action Plan’ (NREAP) (DCCAE, 2010). Finally, analysis of these policy roadmaps can subsequently identify how *enabling measures* can achieve particular emission mitigation targets at a national or sectoral level through ex-ante and ex-post analysis of policies, e.g., regulations placed on car manufacturers, eco-labelling of appliances, etc. (Rogan et al., 2011). This chapter brings together these three aspects in a coherent consistent iterative framework and explores the interactions, the development from one to another, and highlights the need for more analysis on the effectiveness, certainty, and timing of specific measures.

The European Union (EU) face challenges in meeting emissions reduction targets in the short term (to 2020) and establishing realistic targets in the longer term (from 2030 to 2050). The European Commission’s report on moving to a competitive low carbon economy in 2050 predicts that transport will be the most difficult carbon dioxide (CO₂) emitting sector to decarbonise in the long-term, and is the only sector foreseen to have an increase in emissions in the medium-term (European Parliament, 2011a). Efficiency measures and biofuel blending are seen as means of meeting short-term targets (although the latter is limited by blend walls in internal combustion engines (ICE)); however, the primary challenge of decarbonising transport lies in shifting away from petroleum based liquid fuels. There is a clear and urgent need for useful methods to effectively plan and inform the implementation of policy measures to go beyond European short-term targets and address this challenging long-term decarbonisation of the transport sector.

It has become common practice to address this need for planning through the integration of energy models. This integration provides results of greater value by combatting the weaknesses in one model with the strengths of another. This multi-model approach has been adopted and applied to a

number of model types using varying degrees of integration. In its lightest form, two models are run independent of each other with the results of each compared until a convergence is reached giving way to a stronger result set through a low level of model structuring and a more versatile procedure than a fully integrated model, yet is more susceptible to errors arising due to potential inconsistencies between both model types. In the heaviest form, a complete integration of two or more models is carried out, requiring both models to be built within the same mathematical format, combatting the inconsistencies between modelling techniques, yet increasing complexity and processing power. An intermediate form creates a scaled-down representation of the structure of one model in another through integrating a reduced level of detail between model types.

A very common method of this intermediate model integration has been between computable general equilibrium (CGE) models and energy supply models, e.g., the macroeconomic model (MACRO) with a detailed energy supply model (MESSAGE) (Messner and Schrattenholzer, 2000), and a CGE model (GEM-E3) with an energy optimisation model (TIMES) (Fortes et al., 2014). Integration of sectoral specific models have also been evident, e.g., a power systems model (PLEXOS) linked with an energy systems model (TIMES) (Deane et al., 2012), and a three-way integration of MESSAGE, TIMES, and a unit commitment optimisation tool (REMIX-CEM-B) to analyse the potential of concentrated solar power in Brazil (Soria et al., 2016). A broader, long-term analysis of the EU2030 goals was carried out with a similar analysis for Serbia combining the generic optimisation program, GenOpt and the simulation model, EnergyPLAN (Bjelic and Rajakovic, 2015).

There have been very few studies dealing with the integration of transport focused models and broader energy systems models while within those reviewed for this chapter, no representation of the individual policies necessary to achieve the policy roadmaps identified was found. For example, a MARKAL model of household and industry transport activities was integrated with a CGE model and outlined the potential carbon mitigation under a Kyoto target, yet gave no indication of the specific measures required (Schäfer and Jacoby, 2005). A South African based study soft-linked five models to create long-term projections of the transport sector which consisted of developing and linking a CGE model, a vehicle parc model, a time-budget model, a freight demand model, and a fuel demand model. While this study considers the CO₂ mitigation from policy roadmaps (such as shifting from private to public transport), it fails to consider the individual policies measures which may enable this shift (Merven et al., 2012).

The method of model integration presents a concise improvement from individual modelling detail and results, yet there is still a disconnect between modelling and policy analysis as described in the literature review above, especially in the area of transport, which is remarkable given the sizeable task of decarbonising transport necessary to adhere to a low carbon future. This chapter aims to bridge this gap in energy modelling through (i) employing a soft-linking methodology between a least-cost optimisation model of the Irish energy system (Irish TIMES (The Irish Integrated MARKAL-EFOM System) (Chiodi et al., 2013b)) and a sectoral simulation model of the private transport sector in Ireland (the CarSTOCK model (Daly and Ó Gallachóir, 2011b)), similar to the soft-linking methodology used in Chapter 3, and (ii) through using ex-post and ex-ante analysis to determine the specific enabling policy measures. Optimisation models are capable of exploring the implications of different levels of emissions reduction ambition for energy system evolution and can outline potential technology pathways; simulation models can show how particular policies and interim targets can deliver a particular energy system and hence point to policy roadmaps; finally, ex-post and ex-ante analysis facilitate analysis of enabling policy measures. The integration of these modelling and analytical approaches allows for a comprehensive description of how to decarbonise a particular sector, in this case the private car sector in the Irish energy system. The reason Ireland is chosen as a case study is twofold: first, it has the 4th highest transport emissions per capita of all EU member states (in 2014 Ireland was 2.43 tCO₂/capita whereas EU average was 1.62 tCO₂/capita) highlighting the onerous task of decarbonisation (EEA, 2016); second, it has been a case-study for a multi-modelling approach in the past, whereby Irish TIMES was integrated with the power sector (Deane et al., 2012).

This chapter explores an ambitious long term scenario based on the European Commission's recommended CO₂ emissions reduction by 2050 of 80% - 95% relative to 1990 (European Parliament, 2011a). This is in keeping with the Irish national policy position on climate change which declares a long-term vision guided by *"an aggregate reduction in carbon dioxide (CO₂) of at least 80% (compared to 1990 levels) by 2050 across the electricity generation, built environment and transport sectors..."*. A constraint of 80% CO₂ emissions reduction by 2050 relative to 1990 is entered into Irish TIMES, which determines the least-cost solution in all sectors of the economy (agriculture, residential, commercial, industry and transport). This analysis forms the basis for scenario and policy development in the CarSTOCK model, which in turn is used to analyse the type and timing of specific policy measures that can help achieve long-term decarbonisation. The efficacy of enabling policy measures requires individual scrutiny that depends on a multitude of factors which are discussed in this study – who is targeted by the measures, what type of instrument is employed, what is the

timeline of these measures, and what level of change will be required. This chapter is organised as follows, Section 4.2 describes the modelling and analytical methodology, Section 4.3 presents the results, and Section 4.4 concludes.

4.2 Methods

This section first describes and defines technology pathways, policy roadmaps and enabling measures; it then describes the three technical tools employed, namely the Irish TIMES energy systems optimisation model, the CarSTOCK simulation model and ex-post analysis of policy measures; lastly, it describes the multi-model approach that integrates these three tools together.

4.2.1 From Technology Pathways to Policy Roadmaps to Enabling Measures – A Multi-Model Approach

Technology pathways can be broadly defined as the timing, quantity and combination of technologies required to achieve a certain policy target (e.g. an 80% reduction in energy system emissions) by a given end-point (e.g. 2050), e.g., the European Commission's Energy Roadmap to 2050 (European Parliament, 2011a) and the IEA's ETP (IEA, 2016d). They are typically expressed in terms of energy, emissions, and rates of technology diffusion over time (e.g. Megawatt hours, tons of CO₂, % share technologies). Technology pathways are frequently generated in optimisation models that select technologies such that the overall system cost is minimized. In this way, individual sectors (e.g. transport, residential, industry) are optimised according to overall system needs, e.g. what is cost-optimal for the transport sector by itself might be different for what is cost optimal for the transport sector as considered within the entire energy system. Model generated technology pathways will normally need refinement by modellers in order to ensure realism for sectoral results.

Least cost technology pathways purport to model the market dynamics whereby new technologies with the greatest cost advantage are optimally diffused over time. However, in reality, many factors associated with technology diffusion (e.g. information costs, decision-making inertia, inconvenience costs) are not adequately included in the price of the technology. Therefore, policy intervention (e.g. favourable tax incentives) can be required to align the characteristics of low carbon technologies with market signals such that they diffuse at the necessary rate to achieve the policy target. While models that generate technology pathways can be refined to more accurately model technology diffusion (e.g. through a market share algorithm), models that generate technology pathways are usually not designed or equipped to model direct policy intervention.

Policy roadmaps can be broadly defined as a combination of policy goals, such as interim and final % penetration targets, and the strategies for achieving these goals, such as increased energy efficiency, increased renewable energy, fuel switching, etc. e.g., the IEA's WEO (IEA, 2016b), and Ireland's NREAP (DCCAE, 2010). Within a multi-model approach, simulation models with their greater temporal and technical resolution can i) test the feasibility of technology pathways generated in optimization models, and ii) simulate the policy roadmaps that align with these technology pathways. To prepare a policy roadmap based on a technology pathway, each newly diffused technology from the technology pathway must be examined and considered in light of what policy will be expected to facilitate or accelerate its diffusion. In a simulation model a single scenario can be designed to simulate the progressive penetration of a particular technology. The resulting policy roadmap could therefore outline a feasible combination of energy efficiency, renewable energy, and fuel switching - expressed in terms of interim targets at key intervals - that achieve a final overall target.

For certain technologies, an associated policy roadmap will be an almost one to one matching of policy for technology; however, some technologies cannot easily be diffused by one or two policies and for such technologies, a suite of policy measures will be required - policy mixes, especially of different policy types, are usually more successful than single policies (Ó Broin et al., 2015). For technology diffusion, there is evidence that the formative phase for new technologies which are more similar to existing technologies (i.e. more substitutable) and which result in an almost identical energy service are shorter; by contrast, the formative phase for new technologies that are less directly equivalent to existing technologies (i.e. less substitutable) are longer (Bento and Wilson, 2016). Based on these previous findings, it can be predicted that of the range of new technologies in the technology pathways and policy roadmaps analysis, the technologies with less equivalence to incumbent technologies will require larger and more diverse policy mixes and the technologies with greater equivalence to incumbents will require fewer and less diverse policies mixes.

To determine what enabling measures might help diffuse the array of technologies outlined in the technology pathways and policy roadmaps, ex-post and ex-ante analysis of policy measures is used. Ex-post analysis of previous and similar measures can provide important insights from the success rate of previous policies. Energy policies rarely achieve their expected targets – whether overachieving or underachieving. This can be for many reasons, including insufficient incentive. Ex-ante analysis of the policies or combinations of policies likely to succeed are crucial for

decarbonisation strategies to be successful. The iterative process used which flows from technology pathways, to policy roadmaps, to enabling measures is shown in Figure 4.1.

4.2.1.1 Technology Pathways - Irish TIMES Optimisation Model

Technology Pathways have been established in the past using the Irish TIMES energy systems model (Chiodi et al., 2013b). The Irish TIMES model is a partial equilibrium optimisation model of the Irish energy sector, initially developed to build a range of medium and long-term scenarios that provide insights to the technology requirements for energy system decarbonisation. The model was built

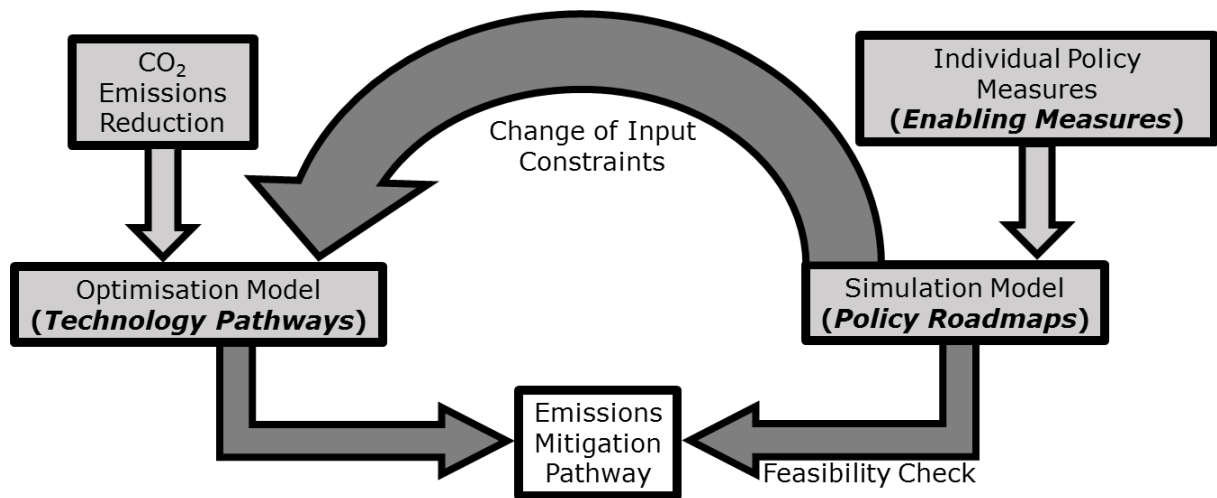


Figure 4.1: Method flow diagram

to provide a technology-rich least-cost linear optimisation basis for the estimation of energy dynamics over a long-term, multi-period time horizon (Loulou et al., 2005). The model simultaneously solves for the least cost solution subject to emission constraints, resource potentials, technology costs, technology activity and capability to meet individual energy service demands across all sectors (see Equation 4.1). The model minimises the net present value (NPV) through the selection of technologies with resulting energy consumption and CO₂ emissions output.

$$NPV = \sum_{t=1}^{NbPer} \left[(1 + \delta)^{1-t} * Annual\ Cost(r, t) * \sum_{a=1}^{NbYrsPerPer} (1 + \delta)^{1-a} \right] \quad (4.1)$$

Where:

δ – Discount Rate; NbPer – Number of periods over the horizon; NbYrsPerPer – Number of years per period; Annual Cost – Sum of all costs; r – Set of regions in the area of study; t – Time period

The Irish TIMES model was built by applying localised data and assumptions to the Pan European TIMES (PET) model, a model of 36 regions of Europe (EU27, Iceland, Norway, Switzerland, and six Balkan countries) (Gargiulo and Ó Gallachóir, 2013). The model represents the potential long-term evolution of the Irish energy system through a network of processes which transform, transport, distribute and convert energy from its supply sector to its power generation and demand sectors. Energy demands are driven by a macroeconomic scenario covering the period to 2050, which is based on the Economic and Social Research Institute (ESRI) Harmonised Econometric Research for Modelling Economic Systems model (HERMES) of the economy which is used for medium-term forecasting and scenario analysis of the Irish economy underpinning the 2013 edition of the ESRI's Medium-Term Review (Bergin et al., 2013b).

The private transport sector in Irish TIMES is driven by exogenous projections of passenger kilometres based on gross national product (GNP) per capita and the number of cars per household coupled with income elasticities of demand determined by the HERMES model. The model chooses from a set of technology and economic attributes that vary over time within the model to meet this demand at least cost while constrained by an overarching long-term reduction in CO₂. Market share of new vehicles is exogenously calculated using a discrete choice model which accounts for tangible costs of vehicles in competition with each other, such as capital costs, fuel cost, and operation and maintenance costs, as well as intangible costs, such as range anxiety, and model availability (see Table 4.1). Further description of the underlying assumptions, corresponding data, and sources of TIMES and of the discrete choice model may be found in Appendix B and Appendix C respectively.

Table 4.1: Discrete choice model assumptions used to calculate market share constraints in Irish TIMES

Technology	2015				2050			
	CC	MC	EC	i	CC	MC	EC	i
Petrol Car	€28,316	€5,598	1.26 c/ltr	-	€28,316	€5,598	1.66 c/ltr	-
Diesel Car	€28,316	€5,598	1.19 c/ltr	-	€28,316	€5,598	1.57 c/ltr	-
BEV	€21,490*	€5,505	0.13 c/kWh	€29,241	€10,041*	€5,505	0.13 c/kWh	€3,843
PHEV	€31,450**	€5,455	0.81 c/ltr	€10,542	€14,695**	€5,455	1.05 c/ltr	-

* Price includes government grant of €5,000 towards Pure Electric Vehicle purchasing

** Price includes government grant of €2,500 towards Plug in Hybrid Electric Vehicle purchasing

4.2.1.2 Policy Roadmaps - CarSTOCK Simulation Model

Irish based policy roadmaps have been established in the past by the CarSTOCK model (Daly and Ó Gallachóir, 2012). The CarSTOCK model is a sectoral simulation model of the private transport fleet in Ireland that projects the evolution of the private car stock, energy use and related CO₂ emissions

from 2013 to 2050 based off the ASIF methodology developed by Schipper et al. (2000), summarised by Equation 4.2. In brief, total private transport related CO₂ is calculated as a sum of the product of vehicle activity (A), private car stock (S), energy intensity (I), and emission factors (F) for fuel type (f) and vintage (v).

$$Transport\ Related\ CO_2 = \sum_{f,v} A_{f,v} * S_{f,v} * I_{f,v} * F_f \quad (4.2)$$

A stock profile is built based off a database acquired from the vehicle registration unit in Ireland which details the evolution of the car fleet between 2000 and 2013 disaggregated by fuel type and vintage of the vehicles. This database was used to create a survival profile for each private car fuel type of varying engine sizes (ES), shown in Figure 4.2 and calculated using Equation 4.3.

$$Survival\ Rate_v^{ES} = Average \left(\frac{(Stock_v^{ES} - Stock_{v-1}^{ES})}{Stock_v^{ES}} \right) * (1 + Survival\ Rate_{v-1}^{ES}) \quad (4.3)$$

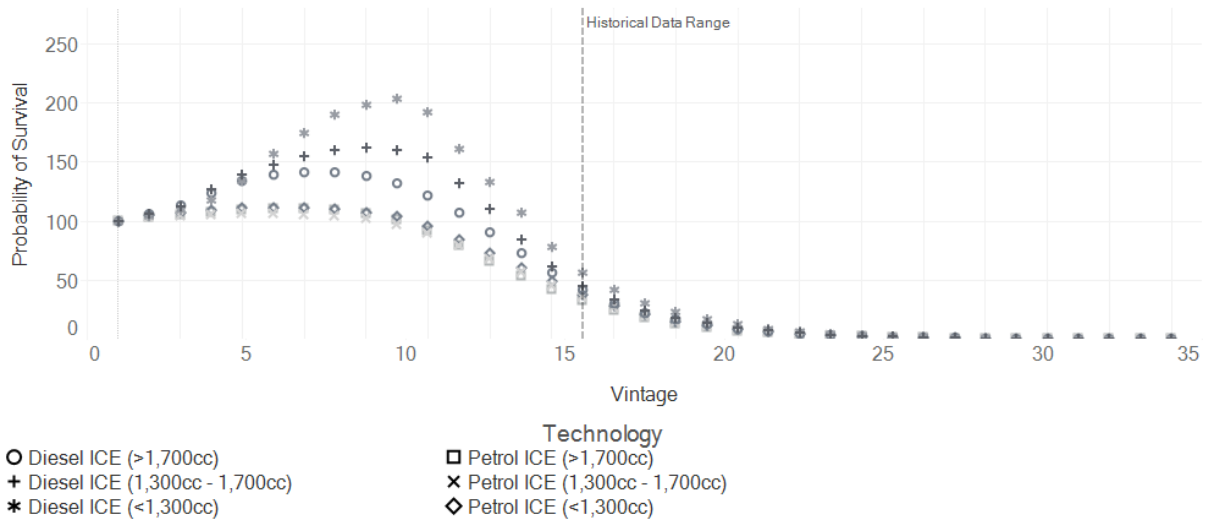


Figure 4.2: Calculated survival profiles for Irish private cars

Mileage and specific energy consumption of the historic fleet, also disaggregated by engine band, were obtained from the Irish national car test results, a compulsory vehicle inspection in Ireland which records data relating to the road worthiness of all private cars on a bi-annual basis for cars under ten years old, and annually beyond this.

The drivers of the CarSTOCK model are generated using the Economic and Social Research Institute (ESRI) long-term macro-economic model HERMES results from the Medium-term review, 2013. These projections are linked with income and fuel elasticities of demand from Johansson and Schipper (1997) (see Table 4.2) to generate long-term stock, sales, and activity projections to 2050.

Table 4.2: Fuel price and income elasticities of demand

Elasticities of Demand	Stock	Vehicle Kilometres	Sales
Fuel Price Elasticity	-0.1	-0.1	-0.1
Income Elasticity	0.35	0.6	1

These projections, linked with the survival profiles and assumptions surrounding mileage and specific energy consumption, are used to generate detailed projections of stock, energy, and emissions using the ASIF method (see Equation 4.2) for the Irish car stock. Finally, market share is calculate exogenously using the market share algorithm outlined in Appendix C as a means of creating realistic shift in national private car market share.

The CarSTOCK model allows for a more detailed evolution of the private car fleet relative to the results from the Irish TIMES model. This proves more effective at presenting an insight to the policies and individual measures which allow for the reduction of CO₂ emissions amongst private cars and subsequently assesses the feasibility of the results from Irish TIMES. For example, Irish TIMES only considers one technology per fuel type, e.g., petrol vehicle or diesel vehicle, while CarSTOCK has the functionality to disaggregate by vehicle type, i.e., small (engine size less than 1300cc), medium (between 1301cc and 1700cc) and large (greater than 1700cc), and even further by vintage. The purpose of this split is to improve heterogeneity through disseminating driving patterns more accurately as owners of small vehicles have been known to drive less per year than those owning larger vehicles (Schipper et al., 2000). Heterogeneity is accounted for using the market share algorithm, in the same way as described in the Irish TIMES model. A more detailed analysis of this, along with additional details of the structure and operability of this model can be found in Daly and Ó Gallachóir (2011b).

4.2.1.3 Enabling Measures - Ex-post and Ex-ante analysis of Policy Measures

Policy measures, with a specific focus on energy efficiency improvement and fuel switching for private cars, were used for scenario development within the CarSTOCK model. These measures were chosen to simulate a corresponding level of decarbonisation against a baseline, which assumes no

policy incentive to switch to alternative fuelled vehicles from the base year onwards, against the low carbon results from the Irish TIMES model. Three measures in particular were focused upon in aiming to achieve the low carbon results as laid out by TIMES; efficiency improvements of ICEs, increased biofuel blending, and measures to promote the penetration of alternative fuel vehicles.

The former two of these policy measures have proved successful in both Ireland and across Europe in the past decade as the target of the measures has been towards suppliers rather than the consumers – towards manufactures for regulations relating to efficiency improvements, and towards fuel suppliers for regulations relating to biofuel. However, the potential of these measures to reduce GHG emissions has been identified to be considerably more limited than that of alternative fuel vehicle penetration, yet the impact of measures encouraging the sale of these vehicles is subject to a much larger degree of uncertainty. Ex-post and ex-ante analysis of these policy measures is used to develop scenarios capable of achieving the policy roadmap laid out by the CarSTOCK model, which assesses the feasibility of achieving a low carbon transport technology pathway as identified by Irish TIMES.

4.2.1.4 Multi-Model Approach

The soft-linking methodology employed in this study can be described as a light form of integration through model coherence, which is graphically represented in Figure 4.1 above and complemented by Table 4.3 below. A long-term CO₂ emission reduction is first entered as a user constraint in the Irish TIMES optimisation model which in turn generates a technology pathway for each sector of the Irish energy system. The technology pathway from the private car sector is extracted, specifically the effects of energy efficiency improvements in the private car fleet and the level of fuel switching, which are used in generating policy roadmaps in the CarSTOCK simulation model with the aim of informing the specific policy measures necessary to meet the technology requirements laid out by Irish TIMES. An ex-ante and ex-post approach, described in Section 4.2.4, is employed to determine the individual policy measures necessary to contribute towards a long-term low carbon scenario.

Table 4.3: Multi-model approach

Model	Approach	Output
Irish TIMES	Optimisation	Technology Pathway
CarSTOCK	Simulation	Policy Roadmap
-	Ex-post & ex-ante analysis	Enabling Policies

4.2.2 Scenario Development

The scenario development of this chapter is initially driven by a low carbon scenario generated by Irish TIMES, providing a cost optimal technology pathway for the transport sector in contributing towards a low carbon future (Section 4.2.6.1). Scenarios are subsequently generated within the CarSTOCK model, identifying the policy roadmaps required to achieve the technology pathway laid out by TIMES, and finally ex-post and ex-ante analysis of measures is carried out to show how to enable measures to achieve this policy roadmap (section 4.2.6.2 – 4.2.6.4)

4.2.2.1 Low Carbon Scenario

An assessment report released from the Inter-Governmental Panel on Climate Change (IPCC) defined CO₂ as “the most important anthropogenic greenhouse gas” with the atmospheric concentration of CO₂ in 2005 significantly exceeding the natural levels ranging over the last 650,000 years. Concerns about GHG emissions interfering with the international climate has resulted in the Copenhagen Accord and the Paris Agreement which established a political consensus on limiting mean global temperature increase to 2°C which must be met through a substantial reduction in GHG emissions. The IPCC 4th Assessment Report shows that to meet this target it is required for global GHG emissions to be reduced by at least 50% by 2050 relative to 1990 levels (IPCC, 2007). The EU has determined that in meeting this target, industrialised countries should contribute more than the average international requirement and have advised between an 80% to 95% reduction by 2050 relative to 1990. This chapter focuses on policy evaluation of the private transport sector using a scenario dealing with a reduction in CO₂ emissions of 80% by 2050 relative to 1990.

4.2.2.2 Improved Efficiency

The most noteworthy policy attempt to steer consumer choice of private cars towards more efficient vehicles in Ireland was from a change in the basis of taxation on motor vehicles in 2008, which was previously based off the size of a vehicle’s engine was changed to correspond to level of emissions from a vehicle (in gCO₂/km) which resulted in a significant migration in the private car fleet to more efficient vehicles (Rogan et al., 2011). This policy measure acted as a supplement to the formal adoption of CO₂ performance standard regulations as decreed by regulation EC 443/2009 of the European parliament which sets a target for specific emissions of 95gCO₂/km to be in effect by 2021 (European Parliament, 2009a). A significant reduction in new car test emissions was experienced across the 28 EU member states in the years following the adoption of these targets (see Figure 4.3) (EEA, 2015).

Energy efficiency improvement policy measures are implemented in CarSTOCK through national targets of new car emissions, with the magnitude of these targets based off the Irish TIMES model. An upper bound is placed on this energy efficiency improvement based off a combination of results from a review of potential vehicle improvements (Kobayshi et al., 2009) and an International Energy Agency study which analyses the max potential improvement in fuel economy in private cars (IEA, 2008). The maximum efficiency improvements of petrol, diesel, and hybrid vehicles by 2050 relative to 2008 was subsequently chosen to be 45%, 47%, and 52% respectively.

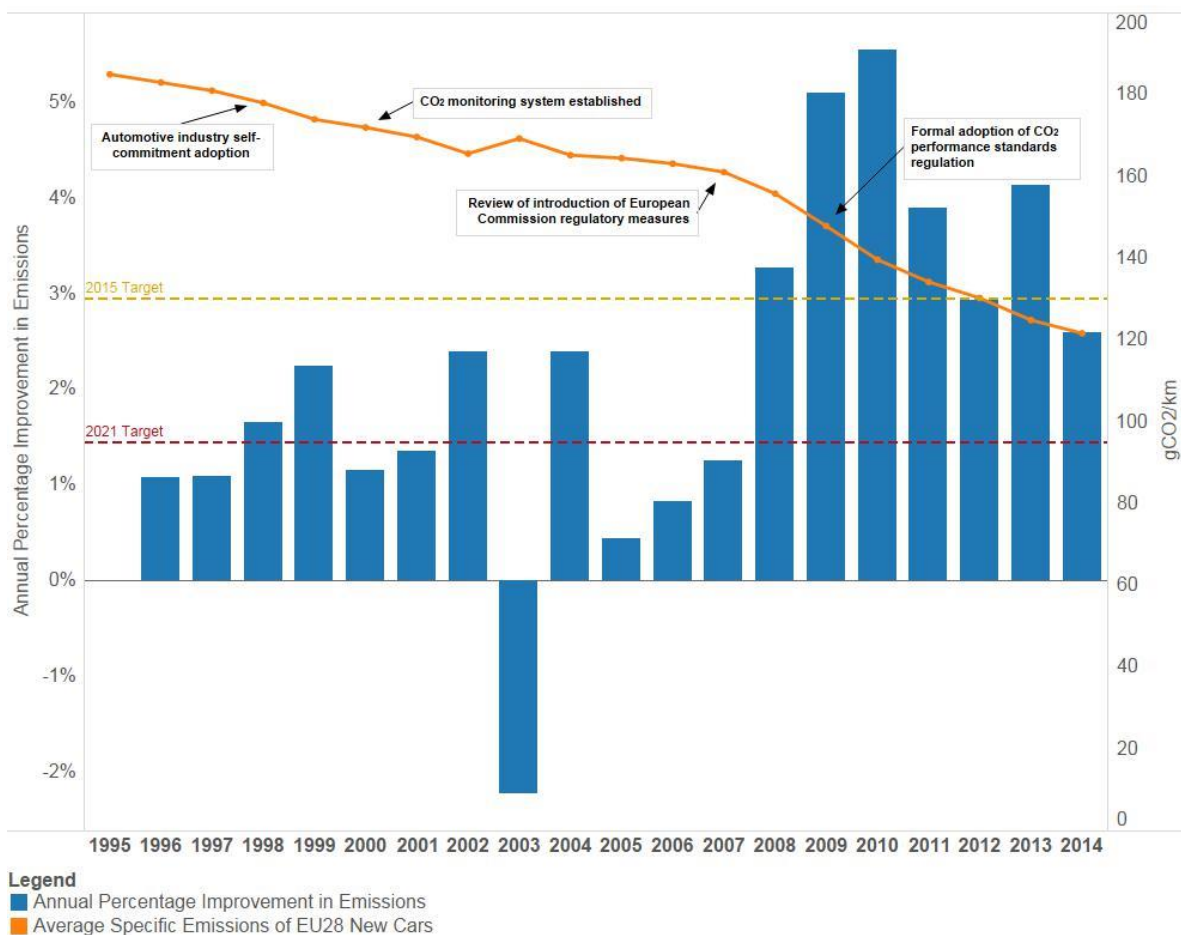


Figure 4.3: EU28 new car emissions in gCO₂/km and annual percentage improvement

4.2.2.3 Biofuel Blending

There has been an increase in the level of bio-ethanol and bio-diesel blending with petrol and diesel in Ireland respectively since the introduction of the Biofuel Obligation Scheme (BOS), which obliges suppliers to derive at least 8.695% of motor fuels placed on the market from a renewable source as of the 1st of January 2017 (White, 2016). This statutory instrument serves as a response to the binding 10% renewable energy in transport (RES-T) target introduced by the Renewable Energy

Directive (RED) in 2009, and to date has proved effective at increasing the level of blending in transport in recent years (Dineen et al., 2014).

Biofuels are effective at contributing towards short term targets, although the relatively lower energy density of bio-ethanol and bio-diesel with respect to their petroleum based counterparts renders achieving the RES-T target solely through the use of biofuel blending to be very difficult.² The yellow band in Figure 4.4 represents the range of possibilities of the RES-T target if it was to be met solely through biofuel blending, the lower limit representing a case whereby the target was to be met through bio-diesel alone (which has a calorific value of 33 Megajoules per litre (MJ/ltr) compared to 36 MJ/ltr for diesel), the upper limit through bio-ethanol alone (which has a calorific value of 21 MJ/ltr compared to 32 MJ/ltr for gasoline), and the centre through a combination (NORA, 2016).

The level of blending of biofuel with petrol and diesel is limited for conventional ICEs to 5% and 7% according to European fuel standards EN 228:2004 and EN 590:2009 respectively, although allowances have been made for both to reach a figure as high as 10% at both a national and regional, level in accordance with the Fuel Quality Directive, for use in conventional ICEs provided sufficient information is made available to the consumer regarding the fuel blend (European Parliament, 2009c). This chapter uses a linear extrapolation of historic bio-ethanol and bio-diesel blending with growth capped at the limits imposed by these European fuel standards in the primary scenario, and a limit placed on the use of biofuels of 10% in the secondary scenario, with the green and blue bands in Figure 4.4 representing the potential of blending using bio-diesel and bio-ethanol respectively.³

The use of Hydrotreated Vegetable Oil (HVO) (also referred to as 'Renewable Diesel') has the potential of overcoming the limitations imposed by the European fuel standards outlined above. HVO is a diesel based fuel traditionally produced from vegetable oils, but recently derived more commonly from waste and residue fat fractions coming from food, fish and slaughterhouse industries, which are hydrogenated and used in an isomerization process to produce a fuel which can entirely substitute diesel (Neste Oil, 2016). The requirement of hydrogen in the hydrogenation process limits the economics of HVO production, therefore this study also uses a scenario

² The RES-T target is an energy based target, meaning a 10% blend of biofuels with fossil fuels will not be enough to achieve 10% RES-T due to the lower calorific value of biofuels relative to petrol and diesel

³ Article 21 of the RED allows for double weightings counted towards biofuels produced from wastes, residues, non-food cellulosic material, and ligno-cellulosic material. Figure 4.4 only considers the weighted value

development based on a range of HVO blending rates to determine its potential long-term decarbonisation effect.

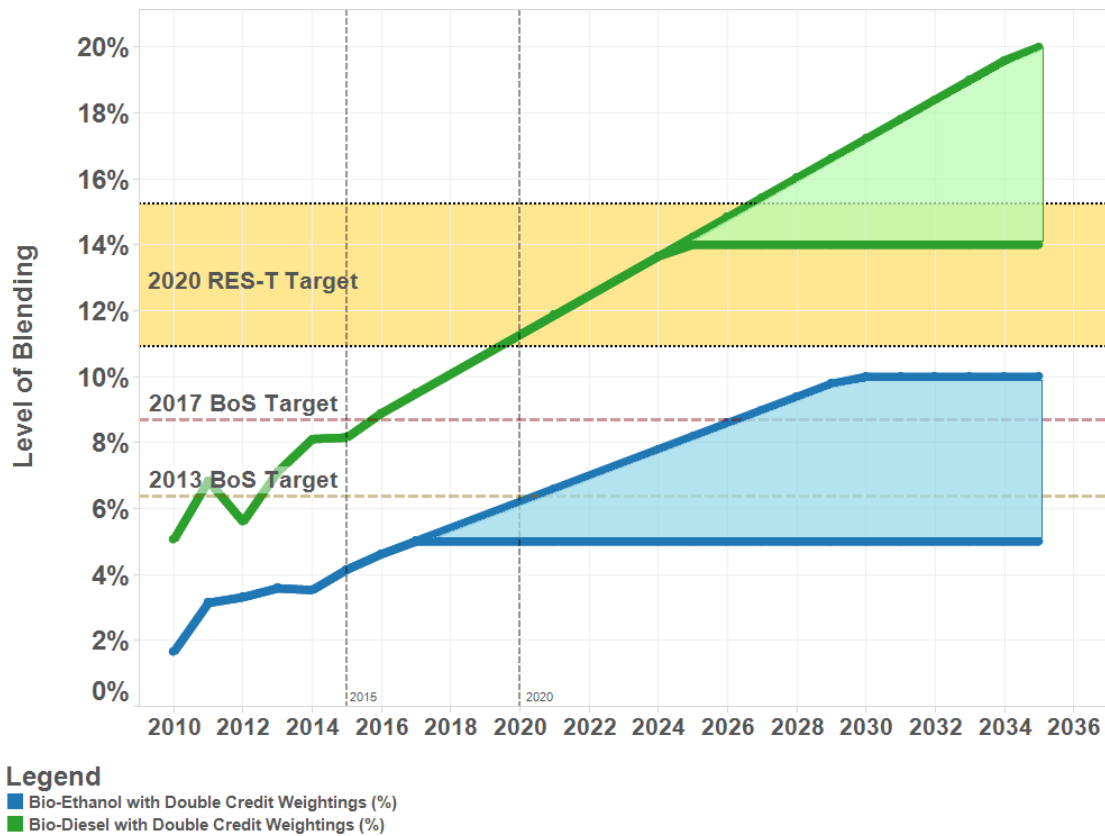


Figure 4.4: Historic and projected bio-ethanol and bio-diesel blending by volume in Ireland. Source: (NORA, 2016)

4.2.2.4 Alternative Vehicle Penetration

The effect of incentivising battery electric vehicles (BEV) and plug in hybrid electric vehicles (PHEV) purchasing through policy measures are considerably more cumbersome to enable when compared against the effects from biofuel blending and efficiency improvement mandates, as the latter two can be enforced on the supply side of the chain while the former relies solely on consumer behaviour. Despite this, a multitude of countries have invested in a myriad of incentivising schemes with the hope of shifting consumer transport preference towards electrification. Norway currently benefits from the highest electric vehicle market share in the world (23% in 2015) (IEA, 2016e). There are a range of contributing factors to this market share – Norway’s high GDP per capita, membership on the Electric Vehicles Initiative board, and strong incentives in the form of tax reduction, e.g., Value Added Tax (VAT) exemption, waivers on road tolls and ferries, and access to bus lanes (IEA, 2016e). Chapter 6 later creates a methodology to deduce the contribution that individual incentives have on shifting consumer preference towards BEVs and PHEVs, although this

chapter employs a simplified method to determine the cumulative tangible and intangible costs faced by private vehicle consumers, and the effect of lowering these costs on national market share.

Figure 4.5 summarises the historic policy measures which have been introduced to encourage BEV purchasing in Ireland. The county of Cork took additional measures to promote BEV purchasing beyond those already offered at a national level which saw a relative increase in sales compared against all other county performance. Despite the cumulative incentives on offer, Ireland is still not on track to meet its (at the time of writing) current 2020 target of 50,000 BEVs (DTTAS, 2017) (see Figure 4.5). This study uses the market share profiles described in Appendix B based on a range of policy roadmaps and later identifies potential contributing policy measures.

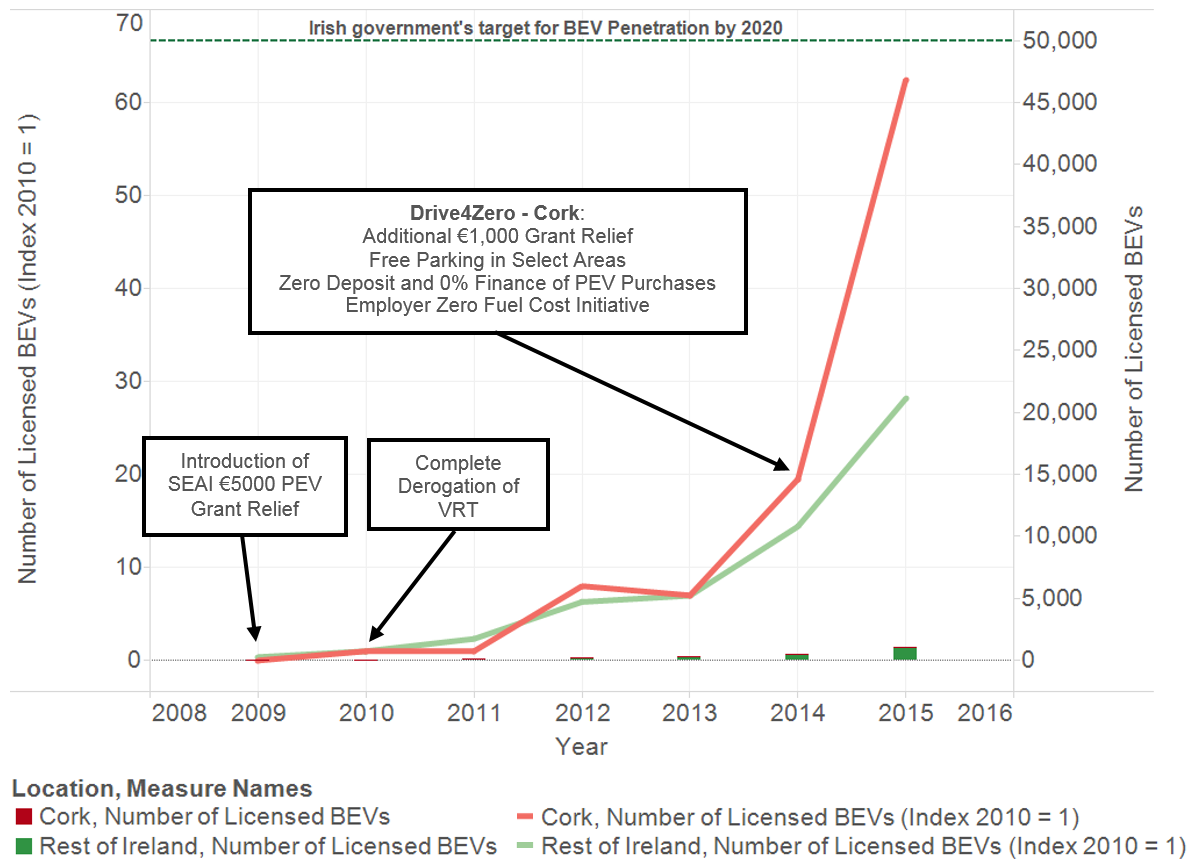


Figure 4.5: Number of licensed BEVs in Cork and rest of Ireland in total and indexed

4.3 Results

The results of the approach outlined above is presented in three distinct sections; *Technology Pathways* – the initial results from the TIMES optimisation model, detailing the optimal technology mix within the transport sector in contributing towards a 80% reduction in CO₂ emissions by 2050 relative to 1990, *Policy Roadmaps* – the results from the CarSTOCK model, detailing the specific

policy packages necessary to contribute towards achieving the technology mix outlined by the TIMES model, and finally *Enabling Measures* – detailing the individual measures capable of contributing towards the policy packages outlined by the CarSTOCK model.

4.3.1 Technology Pathways

In the business as usual scenario, the transport sector sees a ‘dieselisation’ of the private car fleet, which follows the trend experienced in recent years due to the lower level of cost of taxation associated with the relatively lower emissions when compared against petrol (Rogan et al., 2011).

With the 80% CO₂ emissions reduction imposed on the energy system, the private transport sector is determined as a relatively cheap means of decarbonising the energy system, as the TIMES model calculates a substantial 97% reduction of CO₂ emissions in contributing towards the full energy system decarbonisation. The technology pathway created by TIMES under this scenario constraint is calculated in two forms; energy efficiency improvement and penetration of alternative fuelled vehicles. The fuel economy of petrol and diesel cars in 2040 is reduced to 16% and 18% of their 2015 values respectively. Regarding fuel switching, the private transport sector is initially fossil fuel dominated, with plug in hybrids becoming cost competitive from 2020 onwards, achieving a near-full market penetration by 2045, at which point BEVs begin to emerge in the market. The combined effort of these two effects reduce private car related CO₂ emission from 5,940 ktCO₂ in 2015 to 170 ktCO₂ in 2050 (see Figure 4.6).

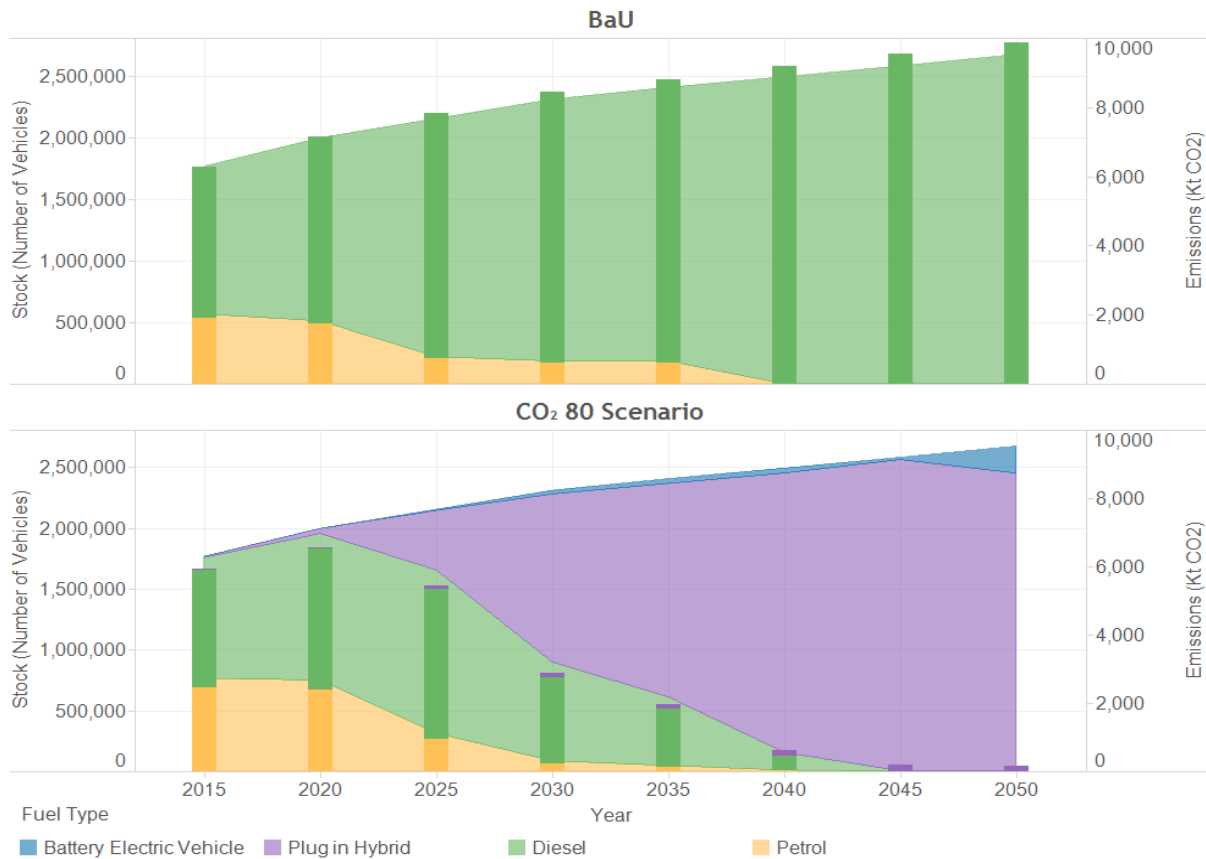


Figure 4.6: Evolution of private car emissions (bar charts) and stock (area chart) over time

4.3.2 Policy Roadmaps

The technology pathways developed in the Irish TIMES model are used to generate a range of policy roadmaps in the CarSTOCK model, capable of satisfying the same level of decarbonisation according to the technology investments laid out by the TIMES CO₂-80 scenario.

The efficiency standards described by the technology pathway above are aimed to be met through a combination of technology efficiency improvements in conventional ICEs (energy efficiency) and an increase in the biofuel blending (carbon efficiency). The former is introduced in the model via a year-on-year fuel economy improvement in keeping with the resultant technology efficiency in TIMES. The latter is represented by altering the fuel composition time series input to signify an increase in bio-diesel and bio-ethanol, described by Figure 4.4. The combined effect of the efficiency improvements contributes towards a decarbonisation reduction level of 4.5% by 2050 relative to 2015 – the improvement in efficiency is roughly offset by the long-term expected growth in vehicle demand. The 2020 RES-T target proves incredibly onerous to be met through biofuel blending alone from the varying energy density of fuel types. In 2015, the gasoline to diesel ratio stood at 1:2.2, yet the relatively lower energy density of bio-ethanol relative to bio-diesel suggests that the rate of

biofuel blending will need to increase at a much faster rate in the short term to represent 10% of transport energy by 2020. Based off the current trajectory, Ireland will not meet its RES-T target.

The vehicle stock rates for each technology are roughly replicated through altering preference rates in the market share algorithm, presenting four unique policy roadmaps. Capital costs, operation and maintenance costs, and fuel costs are held constant for all vehicle types, while the intangible costs are varied for alternative fuelled vehicles presenting 4 unique scenarios for the purpose of this study: (i) 'No Preference Change' where the intangible costs are held constant for all technologies, (ii) 'Gradual Preference Change' where intangible costs for BEVs and PHEVs decrease at a rate of 1% per annum, (iii) 'Rapid Preference Change' where this rate increases to 2%, and (iv) 'Aggressive Preference Change' where this rate increases to 3%. The resulting stock penetration is presented in Figure 4.7 below.

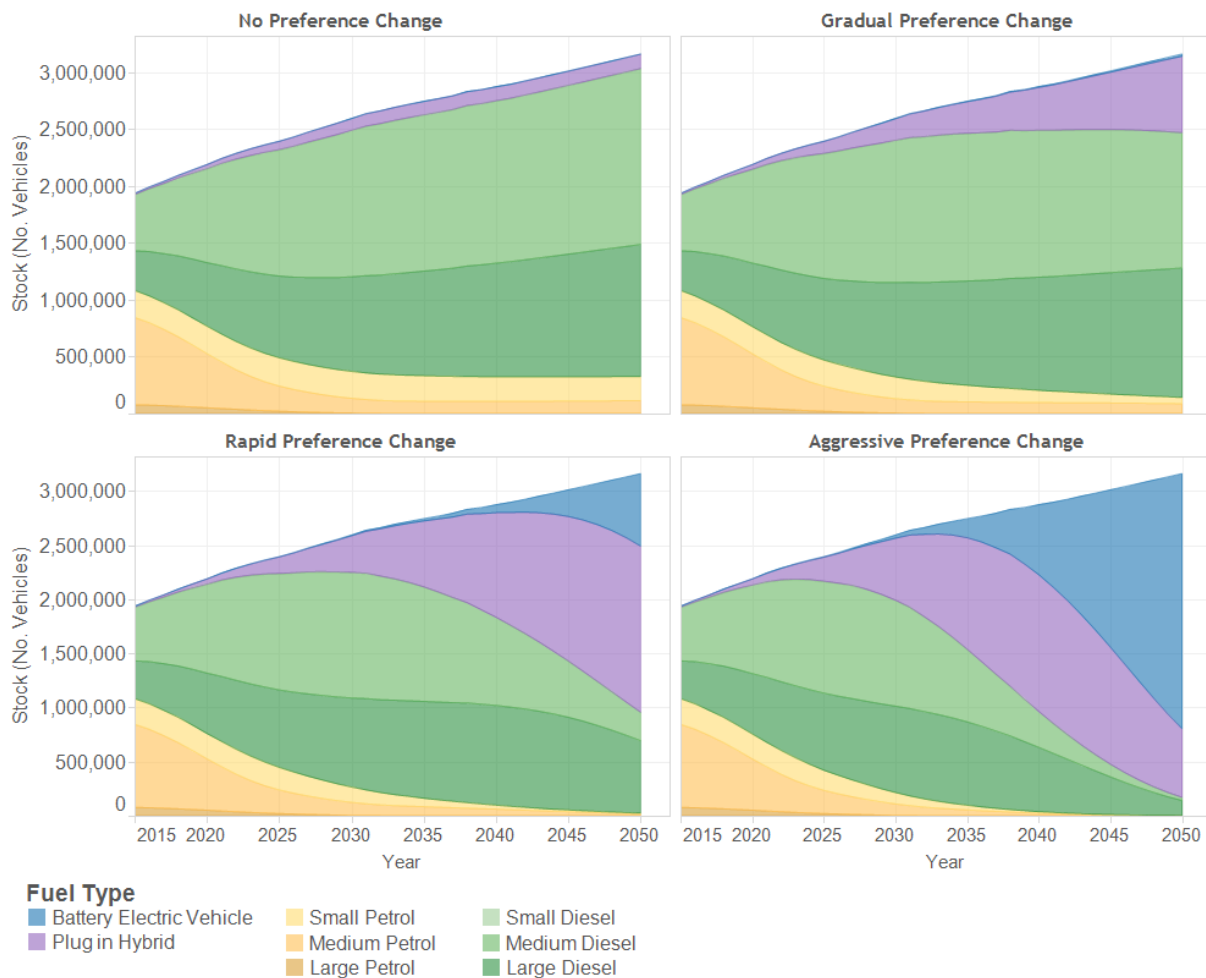


Figure 4.7: Private car Stock profiles under varying preference scenarios

Both the ‘No Preference Change’ and ‘Gradual Preference Change’ scenarios fail to present a significant penetration of PHEVs or BEVs, although preference has a natural shift towards diesel based vehicle technologies over petrol based forms allowing for a second option of decarbonisation to be analysed in the form of increased HVO blending with diesel fuel. A blend of 20% HVO in 2050 has little effect (16.6% reduction, due to the blending limits of biofuel being reached prior to this). A more extreme 100% HVO blend by 2050 has a resultant 92% reduction, achievable due to the aforementioned diesel preference shift. Increased PHEV and BEV penetration contribute towards 17%, 58% and 90% CO₂ reduction in the Gradual, Rapid, and Aggressive Preference Change scenarios respectively (see Figure 4.8). BEVs become notably cost competitive in the latter two scenarios which proves essential in contributing towards a low-carbon policy roadmap.⁴ Combining the ‘Aggressive Preference Change’ scenario with a 100% blend of HVO provides a total maximum decarbonisation of 95% by 2050.

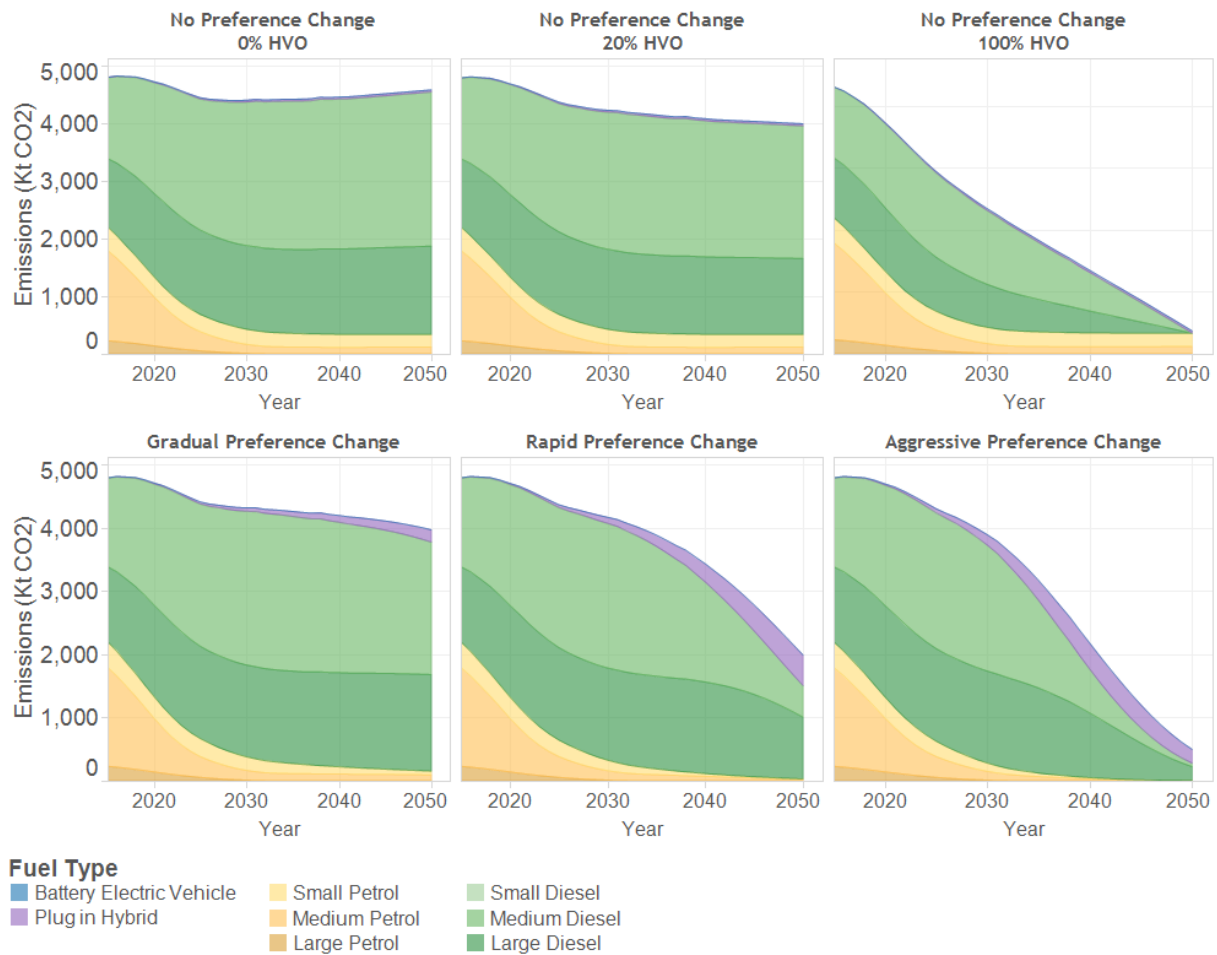


Figure 4.8: CO₂ emission profiles under varying preference scenarios

⁴ For the purpose of this chapter, only the emissions related to the transport sector are considered, in accordance with the UNFCCC reporting standards. CO₂ emissions generated due to the additional electricity generation are calculated within the power sector in TIMES, so only tail-pipe emissions are considered, and is taken as 0 gCO₂/km for BEVs

4.3.3 Enabling Measures

Individual policy measures can be described as either ‘invisible’ measures, requiring an energy transition on the supply side where little or no societal change is required as consumers see no difference – as is the case with mandates on vehicle manufactures and fuel suppliers - and ‘visible’ measures requiring a large societal change to prove effective – such as incentivising electric vehicle purchasing.

Efficiency standards (invisible measures) can be met through an international assignment of CO₂ specific standards, as with the 95 gCO₂/km mandate, of 80gCO₂/km in 2040 and 75gCO₂/km in 2050. Ireland does not manufacture any cars and is entirely dependent on imports, therefore effective implementation of any efficiency improvements vis-à-vis technology alterations is necessary to be mandated at a European level, although a change in the annual motor taxation reflecting these international targets may contribute on a national level.

Domestic policies can be effectively implemented, as they have in the past, in the form of biofuel blending targets (invisible measures). The BoS can be increased further to 10.13% (currently 8.695%) while staying in accordance with the European fuel standards, assuming the same ratio between gasoline and diesel as of 2015. The blending of HVO with diesel is not constrained by any technical limitations and can be increased indefinitely, but is subject to the economics of production providing a suitable policy measure to aid decarbonisation efforts if the preference shift towards PHEVs or BEVs is insufficient.

Policy measures can be introduced to incentivise the sale of PHEVs and BEVs (visible measures), although the effect is not as direct or certain as that of technical efficiency improvements or blending obligations. These measures include, but are not limited to: (i) a reduction or derogation of vehicle registration tax and value added tax, (ii) a reduction of annual parking costs, (iii) improved charging infrastructure, and (iv) further reduction of capital costs via government grant schemes. Mandating these measures has a much lower level of confidence relative to the invisible measures discussed above, due to the reliance on societal transition rather than energy transition on the supply side.

Policy measures may be targeted to consumers (PHEV and BEV purchasing incentives), the suppliers (such as the BoS), and a mixture of suppliers and consumers (car annual registration tax). The effect

on the transportation system of the latter two is much more certain than the former – it is difficult to determine the exact contribution towards consumer preference that these incentives would have.

4.4 Conclusions

The soft-linking methodology employed in this study goes beyond the traditional multi-model approach by combining the foresight and comprehension of the energy system found in a least-cost optimisation model with the detailed technological representation found in sectoral simulation model with ex-post and ex-ante analysis of individual policy measures to enable long-term low-carbon solutions for the sector in question; in essence, this chapter develops and aligns technology pathways to policy roadmaps to enabling policy measures. An optimisation model is capable of determining the least-cost technology pathway to be taken for a given constraint, however it is ill-equipped for informing which policy measures might facilitate this long-term vision, while the technical detail underpinning a simulation model allows for policy roadmap generation. This chapter focused on the private car sector and identified a range of policy measures capable of meeting the technology pathway created by the Irish TIMES model with the CarSTOCK simulation model under an 80% reduction of CO₂ imposed on the entire energy system. Table 4.4 summarises the list of outputs from each iteration of this method.

Table 4.4: Flow of technology pathways to enabling measures

Technology Pathway	Reduced Fuel Intensive Use	Increased Biofuels Use	Increased EVs Penetration
Policy Roadmap	Efficiency Improvements	Renewable Transport Targets	Electrification of Transport
Enabling Measures	CO ₂ Regulation + Car Tax	Biofuel Obligation Scheme	Incentives to Shift Preference

4.4.1 Policy Recommendations

In the short-term, and based on the current diesel-gasoline share, mandatory biofuel blending obligations imposed on suppliers can be increased to 10.13% (which is keeping in accordance with the current fuel quality standards laid out by the European Commission in the RED) to stabilise national private car emissions out to 2025. This blend would have to be further increased to 13.21% to meet current 10% of renewable energy in transport target for 2020, which exceeds the guidelines for conventional ICE diesel and gasoline blends.

In the medium-term, imposing European-wide technology specific improvement targets on car manufactures trending towards 80gCO₂/km in 2040 and 75gCO₂/km in 2050 stabilises CO₂ emissions

in private cars out to 2050, and is sufficient to provide a 4.5% reduction by 2050, relative to 2015, when combined with the aforementioned blending mandates.

In the long-term, an array of incentives can be introduced to promote the use of pure electric vehicles and plug in hybrids, although the effectiveness of these measures is subject to a high degree of uncertainty. In the event of a rapid preference shift towards BEVs and PHEVs (a 2% reduction in intangible costs per annum), there is a consequent 70% penetration of these technologies (split further into 70% PHEV, 30% BEV) by 2050. In an aggressive preference shift (3% reduction in intangible costs per annum), this penetration rate is increased to 95% (21% PHEV, 79% BEV). This level of vehicle electrification satisfies the technology pathways proposed by Irish TIMES, and therefore stands as the cost optimal solution, although due to the level of uncertainty surrounding preference shift, the introduction of HVO blending with diesel fuel is proposed as a secondary long-term solution to decarbonisation. Consumer choice has been switching steadily towards diesel fuelled private cars in recent years (Daly and Ó Gallachóir, 2011b), and HVO stands as a viable means of producing a carbon-neutral diesel substitute allowing for an effective ‘plan B’ in a low-preference shift towards electrification.

The short-to-medium term targets outlined have a higher degree of certainty regarding effectiveness (as ex-post analysis of similar measures have shown relatively successful deployment to date) relative to the long-term electrification measures. A partial explanation may be that in the former, a small number of policies are focused on relatively few actors (the suppliers) whereas in the latter many different policies and policy types are focused on many different actors (the consumers) – this issue is discussed in more general terms below. As an additional policy measure, the blending of HVOs may be targeted towards the suppliers, although the early nature of this fuel type requires further research into costing and feasibility.

4.4.2 Importance of Approach in this Chapter

Studies on the dynamics of technology adoption have made a distinction between substitution and diffusion – the former referring to where new technology simply replaces existing technology, and the latter to where new technology creates new markets and where the existing technology continues to exist, albeit with a reduced niche share (Fouquet, 2008). Ex-post analysis of policies to encourage new technologies have shown that policies where the new technology is a ready substitute for the incumbent have higher deployment rates than policies where the new technology has a greater degree of difference with the incumbent (e.g. the energy service provided by

conventional cars is different in important ways with the energy service of electric cars which goes some way to explaining the latter's limited deployment to-date). The greater the difference between the energy service of the new and existing technologies, the greater the uncertainty about the new technology's rate of deployment. New technologies with greater differences, and thus greater uncertainty, are likely to need more policy attention.

This chapter has shown that policy analysis with simulation models and ex-post analyses of similar policies are useful ways in beginning to lift the uncertainty about new technology diffusion. While there is still an uncertainty surrounding the direct effect one policy measure may have on new technology market share, the methodology presents the potential effect of a group of policy packages, providing an interface capable disaggregating these packages with further research into consumer behaviour. The method has outlined how technology pathways, optimised to least cost, can be complemented with simulation models of policy analysis that align with the least cost approaches but that provide additional understanding on the uncertainty in addition to ways to mitigate that uncertainty. Some technologies will require many policies to support their diffusion and some technologies will require few policies. This inequality between technology and policy has implications for modelling, since for technology optimization models, such as the Irish TIMES energy system model in this study, all technologies are equal when considering adoption, whereas in reality a suite of policies may be required for this adoption of one technology compared to another; simulation models, such as CarSTOCK, are capable of modelling such packages of policy measures. Furthermore, as energy systems models show more radically different energy decarbonisation scenarios (i.e. technologies that are less substitutable equivalents), there is a greater need for multi-modelling and policy analysis approach for all energy sectors.

4.4.3 Future Work and Research

This work has focused on the private car transport sector in Ireland. Modelling capacity already exists or is being developed to extend the work to other sectors (e.g. non-private car transport sector; residential sector, commercial sector). In addition, this work could be undertaken for more ambitious scenarios of overall mitigation potential than the 80% reduction explored in this chapter since the recently ratified Paris Agreement is leading to questions being asked about the validity of an 80% reduction being in line with a "well below 2 degrees" (this topic is covered in the penultimate chapter of this thesis). Further research could involve deepening the analysis with insights for modelling from literature on ex-post analysis of different policy types (Qudrat-Ullah, 2017) and the literature on different policy mixes (Kern et al., 2017, Rogge and Reichardt, 2016) and

how they align with the transition pathways developed by the optimization models. A subsequent soft-link between an energy systems model and a dedicated power systems model would provide useful insights into the effect of electrification of the transport sector would have on the power systems, and would also aid in generating more accurate CO₂ emissions. Above all, this chapter has identified the need for further research into socio-economic modelling methods capable of accurately capturing consumer behaviour in the transport sector, to aid associating the changes in market shares of vehicles following the introduction of purchasing incentives in a modelling framework. Without an accurate socio-economic representation in transportation models, energy modellers are liable to create unrealistic scenarios, and policy makers might offer ill-informed policy measures.

Part II - Socio-Economic Modelling

Chapter 5

Improvements in the Representation of Behaviour in Integrated Energy and Transport Models

Abstract

The inclusion of socio-economic aspects, as human behaviour related to transportation, in Energy-Economy-Environment (E3) models may enable an inclusive representation of the system under analysis, thus providing a more likely representation of reality. This chapter presents a review of integrated energy and transport models characterized by a detailed description of the passenger transport sector and by the presence of transport behavioural features. Firstly, a working taxonomy based on the level of integration of the energy and transport sectors is proposed. As the study underlines, a high level of integration is a precondition for incorporating the consumer behaviour related to purchase decisions and use of transport technologies in energy and transport models. Secondly, the recurring behavioural features related to transport included in current integrated energy and transport models are identified and reviewed: technology choice, modal choice, driving pattern and new mobility trends. The main contribution of this chapter resides in analysing the modelling methodologies adopted in literature to incorporate behavioural features in transport and in examining opportunities and challenges of each of them. Finally, recommendations on model structure and relevant attributes are drawn to consider in relation to consumers' choices in transportation.¹

¹ Chapter based on the submitted journal article: Venturini, G., Tattini, J., Mulholland, E., & Ó Gallachoir, B. P., "Improvements in the representation of behaviour in integrated energy and transport models", *International Journal of Sustainable Transport*, Submitted in January 2017

5.1 Introduction

The dominance of oil use in transport represents a significant obstacle to the transition towards a secure low-carbon energy system: in the past 30 years, global transport energy demand has doubled (IEA, 2014). From 1990 onwards, CO₂ emissions in transport have continued to increase in OECD countries while simultaneously reducing in the industrial and residential sectors, suggesting that current policies to reduce transport demand in OECD countries have been inadequate (IEA, 2009). In addition, transport-related CO₂ emissions in non-OECD countries have doubled over the period 2000 - 2015 due to the increasing level of car ownership and to the growth of freight transport (IEA, 2015).

There are significant efforts underway in OECD and non-OECD countries to decarbonise transport energy use, with a particular focus on car transport. This includes research and technology development programmes by car manufacturers on improving the efficiency of internal combustion engines (ICE), the use of alternative fuels including, but not limited to, compressed natural gas (as a pathway to bio-methane), the electrification of transport, and use of hydrogen fuel cell technology. However, technology development is only one of the dimensions to consider in relation to transport CO₂ mitigation: technology adoption and usage are also key factors and point to a need for individual and collective behavioural analysis.

The IEA proposes a combination of both technological and behavioural measures to address transport CO₂ reduction: avoid, shift and improve (IEA, 2012a). *Avoiding* deals with mitigating the mobility demand, either by teleworking, virtual mobility or other demand-management policies. *Shifting* means increasing the market shares of the most efficient and least polluting modes or increasing the use of car sharing and carpooling. *Improving* focuses on pushing the technology performance improvement and in reducing vehicle specific emissions by decreasing the weight of the vehicle or developing advanced engines.

Energy system models have aided policy makers in determining optimal policies and least-cost pathways towards CO₂ free energy systems (Knopf et al., 2013, Nakata et al., 2011). Previous studies demonstrated the slow pace of decarbonisation in the transport sector relative to other sectors over the last decades (Cayla and Maïzi, 2015, Cuenot et al., 2012, Pietzcker et al., 2014), and highlighted the requirement for both a technological and a behavioural shift (Schäfer, 2012, Waisman et al., 2013). Thus, in order for energy system models to continue being a reliable tool for transport mitigation analysis, it is of primary importance to incorporate individual and collective decision

making, i.e., to represent behaviour. This includes accounting of real household preferences and individual attitudes towards the adoption and use of new technologies and services.

It has become increasingly recognised that energy system models are, in general, effective at improving the representation of techno-economic parameters; however, they are poor at capturing the socio-economic parameters underpinning human behaviour (Schäfer, 2012, Waisman et al., 2013). Li et al. (2015) provide a comprehensive framework for socio-technical energy transitions models, and describe techno-economic detail, explicit actor heterogeneity and transition pathway dynamics as fundamental in considering an exhaustive, and thus more complex, representation of the system. Traditional attempts to address human behaviour in transport mainly consist of reproducing price response aspects of behaviour by means of constant elasticities of substitution and capturing technology adoption via discrete choice models. This chapter builds on and adds value to the work of Schäfer (2012) in three ways. Firstly, by reviewing the state-of-the-art in the integration of energy and transport models, secondly through investigating the modelling methodologies used to incorporate human behaviour (related to transport) and identifying the most commonly incorporated behavioural features, and finally by critiquing these methodologies with a focus on modelling framework and assumptions, time and cost for the data collection, and model integration methodology.

The purpose of this review is to assess the methodologies adopted for including aspects of behaviour in transport within integrated energy and transport models. The overarching goal is to move beyond a review focussing just on model descriptions, and rather to include a degree of analysis and conceptual innovation. Hence, this chapter falls into the category of “critical review” (Grant and Booth, 2009) or, equivalently, “issue review” (Noguchi, 2006). Two main research questions guided the work:

- Structure - how should transport and energy models be structured to allow an effective inclusion of behaviour?
- Parameterisation - what key attributes and parameters should be introduced to represent transport-related consumer choices in an integrated energy and transport model?

The chapter is organized as follows: Section 5.2 illustrates the scope and methodology of the review. Section 5.3 describes the classification criteria for the models analysed, specifically considering the level of integration of energy and transport sectors. As means of overcoming the difficulties of

model integration, model-linking methodologies are also presented in Section 5.3. In Section 5.4, the reviewed models are classified according to the methodology used for introducing the main transport-related behavioural features focusing on technology choice, modal choice, driving pattern and new mobility trends. Section 5.5 draws conclusions by answering the research questions while Section 5.6 provides an overview on the policy implications triggered by the advances in transport behaviour modelling.

5.2 Review Methodology

The critical review methodology comprises a two-stage literature screening process; firstly a broad review of energy and transport modelling literature, and then a more focussed filtering to reveal integrated energy and transport modelling tools that include a representation of transport-related behaviour.

In the initial stage of the study, review articles addressing integrated energy and transport models were used to gather general knowledge on the subject and retrieve additional sources that functioned as guides to the literature (Bhattacharyya and Timilsina, 2010, Connolly et al., 2010, Gargiulo and Ó Gallachóir, 2013, Jebaraj and Iniyar, 2006, Pfenninger et al., 2014, Pye and Bataille, 2016, Yeh et al., 2017). Departing from that first set of models, the analysis was broadened by reviewing relevant journal articles and conference proceedings, selected through wide searches of Internet databases, i.e. Web of Science,² DTU Findit.³ “Energy”, “transport”, “model” and “behaviour” were used as key search terms for screening the body of literature published in the field. The assembled literature was manually screened to filter for alignment with at least one of the following criteria:

- Analysing and modelling the integration of sectoral systems into global and partial equilibrium Energy-Economy-Environment (E3) models.
- Incorporating transport-related human behaviour in an energy model and describing its impact in enabling a more realistic representation of energy systems.
- Using models to evaluate the policy interventions required to support the transition to efficient and climate-aware behaviour in the transport sector.

² <https://www.webofknowledge.com/>

³ <https://findit.dtu.dk/>

As is visible from the chapter structure, the scope of the analysis becomes progressively more focused throughout the review. Section 5.3 investigates the state of the art of the integration of energy and transport models, thus also analysing sectoral models, i.e. partial equilibrium representations of single sectors of the entire economic system. The broader perspective allows a comprehensive view of the features that sectoral-energy and sectoral-transport models are able to capture and the level of detail at which those features can be rendered. In this perspective, 27 energy and transport models from the collected literature are obtained and analysed, and a model taxonomy is proposed, founded on the integration of energy and transport systems. Section 5.4 strictly focuses on the representation of behaviour in integrated energy and transport models, thus limiting the scope to 14 highly integrated energy and transport models.

Within the scope of this review, research focusing on factors influencing behaviour and behavioural theories did not constitute part of the analysis. In the same way, the boundaries of this review lie within energy and transport modelling, hence not considering spatial planning, land and water use and comprehensive environmental assessments, e.g. life cycle assessment (LCA). Moreover, the focus of this chapter is limited to passenger land transport, thus excluding aviation and maritime transport. Regarding the temporal relevance of the models reviewed, only the most recent studies are included (peer-reviewed research published in 2006-2016) for each modelling tool and research team, as well as less recent documents in the case that significant and/or contrasting results were proposed. Although most of the studies analysed focus on European and American countries, no prior limitations were imposed as per the geographical scope of the review, thus aiming to examine comprehensively the modelling efforts of energy and transport systems worldwide.

5.3 Classification of Integrated Energy and Transport Models

5.3.1 Integration of Energy and Transport Models

Modelling plays an important role in the analysis of energy and transport systems, creating a simplified version of a complex system, thereby making it an effective tool for decision making and planning. It is worth noting that energy models do not aspire to predict the exact evolution of the energy system, rather they primarily perform scenario analyses, comparing a number of potential future pathways, which represent a range of possible energy system developments. However, creating models, which are able to capture reality as accurately as possible, is an attempt that should be pursued.

In the field of energy and transport, there are several types of models currently available and in use. Transportation models attempt to capture trends in mobility and help us understand the underlying factors that affect mobility decisions (Lin and Greene, 2010, Rich et al., 2010). Transport energy models (e.g., (Daly and Ó Gallachóir, 2011a, Kloess and Müller, 2011)) evaluate future scenarios of transport energy demand and supply and associated emissions. These tend to be simulation models valuable at assessing the impact of specific policy measures (e.g., (Daly and Ó Gallachóir, 2012)). The expected electrification of the transport sector and the likely increase of fuel blends with higher shares of biofuels will link the future transport sector even more to the overall energy system, offering new opportunities and challenges across the supply-demand balance. Therefore, integrated energy system models, as described in the previous reviews by Bhattacharyya and Timilsina (2010) and Gargiulo and Ó Gallachóir (2013), offer a particularly relevant approach following their capability to analyse synergies, interactions and competitions between different energy sectors and with the surrounding economy. These models represent transport energy use within the entire energy system with a specific focus on technology and seek the least-cost energy system pathway to meet future energy service demands (e.g., (Juul and Meibom, 2011, Merven et al., 2012)). They are used to undertake climate mitigation scenario analysis, comparing impacts on the energy system (including transport energy system) under a range of emissions reduction constraints and for evaluating energy policies. Integrated assessment models (IAM) also seek a least-cost solution to a particular CO₂ emissions constraint, including transport but generally with a less detailed representation of technology (e.g., (Kyle and Kim, 2011, Blanford, 2008, McCollum et al., 2016)). These model types offer a wide variety of approaches available to researchers and decision makers within the energy and transport sectors. In accordance with the focus of the analysis, the scope and level of detail required, the role of the analyst is to assess which model is best suited to cope with each specific aspect.

As this review aims at recognizing the minimum level of integration required for suitably incorporating transport behaviour in energy models, a taxonomy is hereby proposed for usefully describing the level of integration of the transport sector in the reviewed models. While acknowledging that there are no strict boundaries between model classes but rather a gradual change, five model categories are distinguished (Table 5.1): (i) sectoral energy models (E), which consider only the energy-related aspects of the system under analysis; (ii) energy models partially including the transport sector (E+), where the transport sector is represented at an aggregated level; (iii) highly integrated energy and transport system models (E+T), which represent a highly disaggregated level of representation of the transport sector in an energy systems model; (iv)

transport models partially including the energy sector (T+), where the energy system is represented at an aggregated level into a model which has a primary focus on transport modelling; and (v) sectoral transport models (T) which are transport models with little or no focus on energy demand and environmental externalities. Table 5.1 offers a description of the five categories, providing model examples for each. These examples are not necessarily part of the reviewed models, which maintain a closer affinity with the E+T class.

Table 5.1: Taxonomy of energy and transport models

Category	Description	Focus	Examples
E	<i>Sectoral energy models</i> consider only the energy-related aspects of the system under analysis	Study future projections of energy demand, at different levels of spatial and temporal aggregation	Bottom-up building model (Dineen et al., 2015)
E+	<i>Energy models partially including the transport sector</i> have an aggregated representation of the transport sector	Take into account the effect of aggregated transport energy demands on the surrounding energy system.	LEAP (Heaps, 2012) Balmorel (Karlsson and Meibom, 2008)
E+T	<i>Highly integrated energy and transport system models</i> contain a highly disaggregated transport sector in an energy system model	Perform transport-focused policy analyses and consider the effects of modal and technology shift on the energy system	ESME (Pye and Daly, 2015) IMACLIM-R (Waisman et al., 2013)
T+	<i>Transport models partially including the energy sector</i> include the energy system at an aggregated level	Analyse the impact of transport technology and modes on energy consumption and emissions or vice versa	MoMo (Fulton et al., 2009) ICCT Roadmap (Façanha et al., 2012)
T	<i>Sectoral transport models</i> are transport models with little or no focus on energy demand	Simulate travel trips by origin and destination, trip purpose, mode of travel and household demographics. Focus traditionally on behavioural aspects of individuals' decisions	LTM (Rich et al., 2010) MA ³ T (Lin, 2015)



Figure 5.1: Representation of the transport sector in model classes

Figure 5.1 outlines this chapter's hypothesis on the importance of moving from sectoral models (E and T) towards more integrated energy and transport models (E+T) to realistically capture the economic, technical and sociological variables.

Integrated energy and transport models E+T models focus on analysing the potential for the integration of renewable energies in the transport sector (Lund and Kempton, 2008), assessing the challenges of introducing Electric Vehicles (EV) (Bahn et al., 2013, Bosetti and Longden, 2013, Juul and Meibom, 2011, Kyle and Kim, 2011, Seixas et al., 2015), and studying technology and modal shift in the transport sector as a climate mitigation option (McCollum et al., 2016, Pietzcker et al., 2010, Pye and Daly, 2015). On the other hand, E+, E, T or T+ models are often applied for specific sectoral policy and scenario analyses. For the purpose and interest of this review, the focus of this study is limited to the models belonging to the category E+T.

5.3.2 Modelling Approach and Mathematical Method

Energy models are generally classified according to several criteria: Van Beeck (2000) reviewed different ways of categorizing the models, producing a list of nine classification criteria for energy models. Pandey (2002) and Nakata (2004) provide more recent classifications (see Bhattacharyya and Timilsina (2010) for further details), while Lundqvist and Mattsson (2002) comprehensively examine national transport models.

For the purpose of this chapter, the energy and transport models analysed are classified in relation to the modelling approach and mathematical method employed. These two criteria, traditionally adopted for classifying energy models, are here utilized to: (i) comprehend the possible methodologies for integrating the transport sector within an energy system model framework and (ii) explore whether a certain approach should be used for describing both the technological and behavioural dimension.

5.3.2.1 Mathematical Methods – Simulation and Optimisation

According to World Energy Conference (1986), simulation models describe the development of a system based on its logical representation and on exogenously defined assumptions while optimization models apply mathematical programming to determine the optimal configuration of the system subject to some constraint(s). Simulation models are referred to as static if they represent the operation of the system in a single period of time, and dynamic if the output of one period affects the output of subsequent periods. Simulation models are effective at showing how

future energy demand and supply will evolve according to certain trends of energy drivers, or at reproducing traffic in a road network given certain household characteristics. Concerning transport modelling, these tools can usefully simulate the impact of specific policy measures, as for the model UKTCM (Brand et al., 2012).

Energy systems models, also referred to as partial equilibrium models, are a particular branch of optimization models that find an equilibrium solution for the energy system alone. This contrasts with general equilibrium models, including Computational General Equilibrium (CGE) models (Hosoe et al., 2010), where a general equilibrium across the entire economy is achieved. Optimization models are useful for determining potential least-cost solutions to meeting a specific policy goal, e.g., an emissions reduction target.

5.3.2.2 Modelling Methods – Top-Down and Bottom-Up

The second classification criteria considered relates to the level of detail in the description of commodities and technologies of a system, leading to two major classes: top-down (TD) models and bottom-up (BU) models. The former class of models focus mainly on the macroeconomic dimensions and aims at capturing the economic influence of prices and markets on the energy and transport sectors using a number of economic variables as drivers for service demands. The TD modelling approach can be effective at providing technology roadmaps but lack the level of detail required to determine the individual policy measures to meet these results.

BU modelling seeks to provide a more technologically rich representation of demand and supply. These can be (either single or multi-sectoral) simulation models (e.g., (Daly and Ó Gallachóir, 2011a)) or full energy systems optimization models, e.g., MARKAL (Loulou et al., 2004) and MESSAGE (McCollum et al., 2014). Within BU models, existing or under development technologies are characterized along the entire supply chain by means of technical, economic and environmental parameters. The energy system is then represented as a network of technologies and commodities, called a Reference Energy System (RES). BU energy models are commonly partial equilibrium models, i.e., they consider only one aspect of the energy system. The macroeconomic background remains vaguely defined and the relationship between the energy and the outside sectors with the rest of the economy is simplified. This results in a high level of detail surrounding one sector but fails to give the same foresight of the complete economy as TD models.

TD and BU modelling approaches complement each other: the aspects where TD models reveal weaknesses are often those where BU are stronger (see Chapter 3 and 4). Therefore efforts have been put in creating the so-called hybrid models (Hourcade et al., 2006). Such modelling approach can be either based on increasing the technological detail of conventional TD models (as for instance in the models WITCH (Bosetti and Longden, 2013), ReMIND (Pietzcker et al., 2010) and IMACLIM-R (Waisman et al., 2013)), or on including a more detailed representation of the macroeconomic background in BU models (e.g., the models CIMS (Horne et al., 2005) and GCAM (Kyle and Kim, 2011)). Some models are more difficult to classify but are most readily also grouped in the hybrid category, including some integrated assessment models (e.g. the model MERGE (Blanford, 2008)) and other types of hybrid models (e.g. the model PRIMES (E3MLab/ICCS, 2014)).

5.3.3 Discussion on Energy and Transport Model Integration

A classification of the reviewed integrated energy and transport models (E+T), according to geographic scope, time horizon, mathematical method and modelling approach is presented in Table 5.2.

The vast majority of the studies are used for long-term analyses with a time horizon of 50-100 years, as evident from Table 5.2. This observation is in line with the fact that energy and transport models are often developed to assess optimal long-term pathways towards a certain environmental goal and to inform decision makers early in advance of policies and measures which can be efficient and effective in the long run. On the other hand, sectoral transport models (T) often focus on traffic assignment in a shorter run, due to e.g. the underlying uncertainties on the future development of the road infrastructure.

With regards to the geographical scope, 12 out of the 27 studies reviewed have a country scope, 10 have a global outlook, 3 are developed at regional level, and 1 at city level. However, many of these models are adaptable to different geographical contexts (see the open source energy system model OSeMOSYS (Howells et al., 2011)) and can be applied to perform comparative studies for different countries (Mittal et al., 2016, Zhang et al., 2016). Some of the models (e.g. PRIMES-TREMOVE (E3MLab/ICCS, 2014), TRAVEL (Girod et al., 2012) and UKTCM (Brand et al., 2012)) are detailed representations of the transport sector, which can be linked or integrated within a wider energy system model. In this latter case, mathematical method and modelling approach refer to the more detailed transport module.

Table 5.2: Classification of integrated energy and transport models

Model Name	Geographic Scope	Time Horizon	Mathematical Method	Modelling Approach	Focus	Reference
AIM/End-use	China India	2010-2050	O	BU	Comparison of low carbon urban transport scenarios for China and India	(Mittal et al., 2016)
Balmorel	Nordic and Baltic countries	Year 2030 with hourly resolution	O	BU	Creation of a road transport add-on to traditional Balmorel model, to assess integrated power and transport systems and vehicle to grid	(Juul and Meibom, 2011)
BLUE	United Kingdom	2010-2050	S	H	Dynamic stochastic simulation of technology diffusion, energy and emissions	(Li and Strachan, 2016)
CIMS	Canada	2005-2035	S	H	Modelling technological changes in a more behaviourally realistic manner in order to facilitate policy analysis for a greater range of technologies	(Horne et al., 2005)
COCHIN-TIMES	California	2005-2050	O	BU	Demonstration of a practical approach for incorporating behavioural effects from vehicle choice models into E4 models	(Bunch et al., 2015)
ECLIPSE	Global	2000-2100	CGE	H	Development of an integrated energy-economy model with a detailed transport sector representation	(Turton, 2008)
EnergyPLAN	Denmark	Year 2020 with hourly resolution	S	BU	Integration of renewable energy into the transport and electricity sectors through vehicle-to-grid technology	(Lund and Kempton, 2008)
EPPA	Global	2005-2050	CGE	TD	Disaggregation of the passenger vehicle transport sector in a CGE model	(Karplus et al., 2013)
ESME	United Kingdom	2010-2050	O	BU	Representation of endogenous mode shift for urban passenger travel in a whole energy system model	(Pye and Daly, 2015)
ExSS	Ahmedbad, India	2015-2035	S	BU	Analysis of co-benefits of low-carbon passenger transport actions in an Indian city	(Pathak and Shukla, 2016)
GCAM	Global	2005-2095	S	BU	Long-term effect of alternative vehicles on greenhouse gas emissions and energy demand	(Kyle and Kim, 2011, Mishra et al., 2013)
GET-R	Global	2010-2100	O	BU	Analysis of fuel and vehicle technology choice for passenger transport under CO ₂ targets	(Grahn et al., 2013)
IMACLIM-R	Global	2001-2100	CGE	H	Implications of modelling non-price determinants of mobility	(Waisman et al., 2013)
Irish TIMES CA-TIMES	Ireland, California	2005-2050	O	BU	Incorporating modal choice within passenger transport in a TIMES model	(Daly et al., 2014)

MESSAGE	Global	2005-2100	O	BU	Introduction of consumers' heterogeneity and non-monetary parameters	(McCollum et al., 2016)
OSeMOSYS	User-dependent	User-dependent	O	BU	Description of the open source energy system model	(Howells et al., 2011)
PET36	Europe	2005-2050	O	BU	Assess the cost-effectiveness of electric vehicles in European countries	(Seixas et al., 2015)
PRIMES-TREMOVE	Europe	2005-2050	S	BU	Advanced transport module for scenario and policy analysis of the European transport sector, stand-alone or fully linked with PRIMES energy model	(E3MLab/ICCS, 2014)
ReMIND	Global	2005-2100	O	H	Analysis of technology and mode shift as different mitigation options for the transport sector	(Pietzcker et al., 2010)
SATIM	South Africa	2006-2050	O	BU	Describing the TIMES model of the entire energy system in South Africa	(Merven et al., 2012)
TIAM-UCL	Global	2010-2100	O	BU	Explore the competitive and/or complementary relationship between hydrogen and electricity, with endogenous technological learning	(Anandarajah and McDowall, 2015)
TIMES California	California	2005-2050	O	BU	Assess least-cost mitigation options required to meet California's long-term 80% greenhouse gas emission reduction goal, by considering all the energy sectors	(McCollum et al., 2012)
TIMES Canada	Canada	2007-2050	O	BU	Perform policy analysis for promoting electrification of road transport in Canada	(Bahn et al., 2013)
TRAVEL	Global	2010-2100	S	BU	Predict global travel demand, modal split shifts, and changes in technology and fuel choice	(Girod et al., 2012)
UKTCM	United Kingdom	2010-2050	S	BU	Policy analyses and low carbon strategy development for the transport sector	(Brand et al., 2012)
US-TIMES China-TIMES	US China	2010-2050	O	BU	Comparison of transport scenarios between China and US, with focus on technological shift	(Zhang et al., 2016)
WITCH	Global	2005-2100	O	H	Review of the electrification of light duty vehicles within a model that utilizes a learning-by-researching structure	(Bosetti and Longden, 2013)

Notes: S: simulation, O: optimization, CGE: computable general equilibrium, BU: bottom-up, TD: top-down, H: hybrid

Figure 5.2 reports a cross classification for the 27 reviewed studies, according to modelling approach and mathematical method. Most 'E+T' models considered fall in the category of optimization models (16), while amongst the remaining, 8 are simulation models and 3 are CGE. Among optimization

models, the majority are BU models (14), while 2 belong to the hybrid type. Once more, the TD approach is traditionally used in macroeconomic models, where the energy and transport systems appear at a more aggregated level. Hence, an 'E+T' model with a detailed representation of the transport system is often not possible or not pursued.

Transport models 'T' and 'T+', focusing on the factors that affect mobility decisions, are mainly based on a simulation method. On the other hand, the review highlights that most of the 'E+T' models adopt an optimization method. Therefore, when the aim is to incorporate transport behavioural features in energy models, the challenge of combining a simulation approach within a traditional optimization model structure needs to be considered. For instance, the structure of the nested multinomial logit model MA³T (Lin, 2015, Lin and Greene, 2010) is replicated in the optimization model COCHIN-TIMES (Bunch et al., 2015).

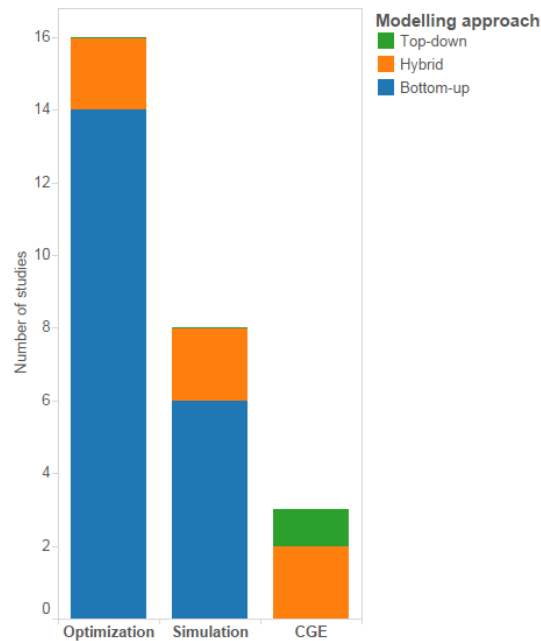


Figure 5.2: Mathematical method and modelling approach of the reviewed E+T models

Six out of the 27 reviewed references are hybrid models, which combine the top-down with the bottom-up approach. As further highlighted in Section 5.4, hybrid models better allow introducing a detailed modelling of technological, macroeconomic and microeconomic characteristics of the energy system. Nevertheless, modelling and computational difficulties may arise when introducing several parameters and constraints in one single model framework. Therefore, most attention has been set on integrating the various approaches through model linking with the aim to harness the richness of each model type through the creation of an interaction. Section 5.3.4 provides a

comprehensive review of the model linking techniques used between energy models with a focus on the linkage between energy and transport models.

5.3.4 Model Linking Methods

Combining different modelling approaches can take advantage of the strengths of individual methodologies and add value and insight to individual approaches. Model coupling methodologies can be classed by means of operation (as done by Labriet et al. (2015) and Böhringer and Rutherford (2009)). This chapter splits these methodologies into three classes: (i) Independent Model Convergence, (ii) Partial Integration, and (iii) Full Integration. Model linking methods can be used as a means of improving the representation of behaviour into a model which previously neglects this area, with examples found below. A definition of each class follows, with a detailed focus on soft-linking between energy and transport models.

5.3.4.1 *Independent Model Convergence (IMC)*

Under IMC operation, two models are run independently of each other and done so until a convergence is reached. This methodology requires the least level of structuring of the models among the three classes and has been identified as a faster and more versatile procedure than a fully integrated model; however, it is much more susceptible to errors arising due to inconsistencies between models. Chapter 3 carried out this approach between a sectoral simulation model of the private car fleet and the Irish TIMES energy system optimization model to determine the magnitude of the policy measures which would be required on an annual basis for this sector to contribute to an overall 80% CO₂ reduction by 2050, relative to 1990. Daly and Ó Gallachóir (2011a) carried out a similar approach, considering a soft-link between these two models with a more specific focus on the underlying modelling principles and projections of energy service demand.

5.3.4.2 *Partial Integration (PI)*

PI involves the integration of some detail from the bottom-up model into the top-down model, or vice-versa, to create a scaled-down representation of one model in the second. By far, the most common approach is the integration of bottom-up data into a top-down model, generally to improve sectoral representation into a CGE model, which is the case in Schäfer and Jacoby (2005) who carry out this methodology with a specific focus on the transport sector. In this study, a modal shift model and a MARKAL model of household and industry transport activities (bottom-up) are integrated into a CGE model (top-down) to provide an analysis on the penetration of new automobile technologies. This method found an inconsistency between energy use with bottom-up and top-down models due

to errors in calibration, although Kiulla and Rutherford (2013) address this inconsistency by providing an ‘as best as possible’ match between models. Similarly, Merven et al. (2012) soft-linked five models to create long-term projections of the transport sector in South Africa. This consisted of developing and linking a CGE model, a vehicle parc model, a time-budget model, a freight demand model, and a fuel demand model. The outputs from the CGE model (i.e., GDP levels) were used to provide the baseline scenarios for the vehicle park and freight demand models, while the fuel demand and time-budget models improved the representation of behaviour used in long-term projections.

5.3.4.3 Full Integration (FI)

The least common of all coupling methods, FI operation is carried out by a complete integration of both models, requiring both to be built within the same mathematical format. This combats the inconsistencies between top-down and bottom-up modelling techniques, yet requires increased processing power. No cases of this method were found within the transport sector, although a few examples are found using other sectors. A pedagogic analysis is carried out in Böhringer and Rutherford (2008) which praises the coherence of this integration, but identifies the limitations associated with dimensionality between models. A second approach is considered in Böhringer and Rutherford (2009) which decomposes the integrated mixed complementarity problem (MCP) formulation to successfully address the problem with dimensionality. Lanz and Rausch (2011) further employ this decomposition method in modelling U.S. climate policy. This method of model linkage is also known as ‘hard-linking’, while the previous two methods are ‘soft-linking’ methods.

5.4 Transport Behaviour in Energy and Transport Models

Although energy system models are capable of acting as effective decision-making tools by providing valuable insights into the dynamics of the different energy sectors, they may not always be fully comprehensive. Jaccard et al. (2003) accurately described the level of comprehension in an energy system model:

“An ideal energy system model should include technological explicitness, microeconomic realism and macroeconomic completeness”

Technological explicitness refers to the quality of including a vast amount of information about the performance of technologies. *Microeconomic realism* relates to a realistic representation of

consumer behaviour when dealing with decision-making. This requires the model to be able to include not only the description of techno-economic parameters, but also of other attributes related to socio-economic aspects. *Macroeconomic completeness* refers to considering the feedback of the dynamics and transformations occurring in the energy system on the rest of the economic sectors. Although a holistic analysis should comprehend all three of these dimensions, the majority of energy models fail to do so. As illustrated in Section 5.3, model linking and hybrid models currently represent the only approaches for merging these three characteristics in a single modelling framework. This section explores the dimension of *microeconomic realism* proceeded by examples to date, specifically addressing consumer behaviour related to purchase decisions and use of transport technologies.

Schäfer (2012) reviews and identifies the lack of behaviour representation in energy models, suggesting the inclusion of five main features to simulate behavioural change in transportation: elastic transportation demand, endogenous mode choice, choice of no physical travel, infrastructure capacity representation, and segmentation of urban and intercity transport. His study indicates that a considerable investment in research and development is required for a breakthrough in the specifics of new technologies for achieving CO₂ reduction. At the same time, the behavioural dimension is also fundamental: new technologies have to be accepted by people and therefore it is important to include a description of the real household preferences, their behaviour when taking decisions, and their acceptance of different transport technologies in energy models. Furthermore, empirical results show a link between lifestyle and sustainability in travel behaviour, calling for a paradigmatic shift in transportation policy from capacity/demand management towards lifestyle adjustments (Fan and Khattak, 2012).

Consumer choice is generally not accurately represented in energy models: either the transport market shares are endogenously determined accounting only for the life cycle costs of the different alternatives, or they are exogenous inputs deriving from the assumed consequence of some energy policy, such as in Bahn et al. (2013). In this second case, Bunch et al. (2015) illustrate that there is a gap between the real consumers' preferences and the assumed market shares in the scenarios. As a response to the limitation of the energy system models highlighted in Schäfer (2012), there has been a recent trend in attempting to integrate behavioural transport models within larger E3 models (Waisman et al., 2013). Instead of performing traditional "what if" scenario analysis, the research interest has shifted to the endogenization of modal and vehicle choice in a behavioural realistic manner (Bunch et al., 2015, Daly et al., 2014). Such approaches require both modal and vehicle

shares to be selected not only according to a cost optimization, but also including other factors, e.g., travel time and infrastructure availability. As an additional trait of behavioural realism, the representation of population heterogeneity is increasingly represented in 'E+T' models. A much more realistic result is achieved when the consumers are disaggregated by classes according to their access to technology, their level of demand and their income, as demonstrated by Cayla and Maïzi (2015) for the residential and transport sector.

The purpose of this section is to review the most remarkable features incorporated in energy and transport models (E+T) to represent transport behaviour. From the 27 models reviewed in Section 5.3, 14 studies have been further analysed as they include some of the transport behavioural aspects identified.

5.4.1 Behavioural Features

The recurring ways to include behaviour in energy and transport systems have been classified in the four categories: (i) Technology choice, (ii) Modal choice, (iii) Driving pattern, and (iv) New mobility trends.

The rationale behind the selection of these features departs from the works by Schäfer (2012), Li et al. (2015) and McCollum et al. (2016), examining the recurring applications related to behaviour introduction in current energy and transport models, and identifying new and complementary attributes.

- i. *Technology choice* represents the possibility for a model to endogenously select a particular transport technology from a set, based on cost and non-cost parameters. More specifically, to represent consumers' behaviour, non-monetary factors are commonly utilized. The concept of technology choice is typically applied to the choice of road vehicles.
- ii. *Modal choice* represents the option for the model to endogenously determine the market shares of the different transport modes. This represents a powerful feature when studying the potential for future modal shift to more sustainable transport modes, such as the shift from private cars to public transport or to non-motorized modes.
- iii. *Driving pattern* is generally defined as the speed profile of the vehicle, but can be expanded to include other aspects of driving behaviour, such as eco-driving (Ericsson, 2001), or simply distance travelled in a certain period.

- iv. *New mobility trends* include recent developments in the use of transport systems, fostered by the introduction of different services and Information and Communication Technology (ICT) applications. Advancements in this area allow consumers to better manage their trips including phenomena such as intelligent transport systems, car sharing, carpooling, trip chaining, autonomous vehicles, mobility as a service (MaaS) and optional transport abdication.

Modal choice and *technology choice* are more commonly included in 'E+T' models than the other categories. However, analyses show that the potential emission reduction achievable by promoting car sharing and carpooling is high. In fact, by increasing the occupancy factor of light-duty personal vehicles from the current value for Denmark of 1.55 person/vehicle and for Ireland of 1.49 person/vehicle to a desirable value of 2 person/vehicle,⁴ the reduction in overall CO₂ emissions for the transport sector would be 15% in Denmark and 25% in Ireland as a yearly average over the period 2015-2050.⁵ Such a significant potential constitutes the rationale for including *new mobility trends* among the transport behaviour aspects considered in the review. Moreover, modelling *driving patterns* can improve the representation of the road transport sector and its influence on the whole energy system, since driving pattern affects the emission and fuel use of vehicles.

5.4.2 Discussion on Behavioural Features Representation

The four behavioural features identified in the 14 'E+T' models reviewed are presented in Table 5.3, while advantages and disadvantages of the various methodologies are discussed in the remainder of this section. As summarized in Figure 5.3 below, 12 of the 14 models reviewed include a representation of modal choice, 9 represent technology choice, 5 of them model driving pattern and only one deals with new mobility trends.

⁴ The European Environment Agency showed that values close to 2 for car occupancy have been reached in some European countries in 2008. Hence, the value has been chosen to represent carpooling as an important phenomenon in the two countries

⁵ The analysis has been performed with the bottom-up optimization energy model TIMES-DK for the period 2015-2050 for Denmark, and with the bottom-up sectoral simulation model CarSTOCK for Ireland

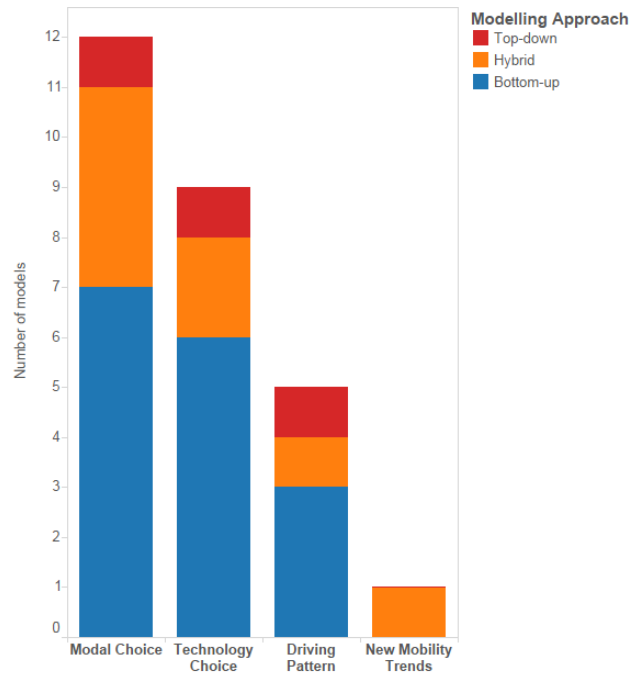


Figure 5.3: Distribution of the modelling approaches across the four behavioural features

This analysis underlines the reason behind the easier applicability of concepts as technology choice and modal choice with respect to fewer implementations of driving pattern and new mobility trends. Among the reviewed studies, hybrid models have the potential to capture all the four behavioural features, although the scope of the analysis determines the appropriate level of detail for each characteristic. Hybrid models, e.g., CIMS (Horne et al., 2005), IMACLIM-R (Waisman et al., 2013) and ReMIND (Pietzcker et al., 2014), specifically build a framework able to investigate trends across different systems or knowledge domains. Therefore, they are meant for carrying out cross-disciplinary analyses and give answers to research and policy questions from a broader perspective. To limit model complexity, these gains could come at the expense of a more aggregated representation of reality. On the other hand, bottom-up and top-down models often address a specific energy and transport policy issue, e.g. as for EPPA (Karplus et al., 2013), ESME (Pye and Daly, 2015) and UKTCM (Brand et al., 2012). In this case, models can provide robust insights on a certain phenomenon, as the future potential for modal shift (Girod et al., 2012) or the acceptance and penetration of electric vehicles in the transport sector (Bunch et al., 2015).

Table 5.3: Representation of transport behavioural features in energy and transport models

Model Name	Technology Choice	Modal Choice	Driving Pattern	New Mobility Trends	Modelling Approach	Reference
BLUE	Intangible costs/benefits Hurdle rates	-	-	-	H	(Li and Strachan, 2016)
CIMS	MNL	MNL	-	MNL	H	(Horne et al., 2005)
COCHIN-TIMES	Disutility costs	-	Driving profiles	-	BU	(Bunch et al., 2015)
ECLIPSE	-	TTB	-	-	H	(Turton, 2008)
EPPA	Nested CES	Nested CES	E	-	TD	(Karplus et al., 2013)
ESME	-	TTB	-	-	BU	(Pye and Daly, 2015)
GCAM	NMNL	LM	-	-	BU	(Kyle and Kim, 2011, Mishra et al., 2013)
IMACLIM-R	-	TTB CES	E	-	H	(Waisman et al., 2013)
Irish TIMES CA-TIMES	-	TTB, TTI	-	-	BU	(Daly et al., 2014)
MESSAGE-TRANSPORT	Disutility costs	MNL	Driving profiles	-	BU	(McCollum et al., 2016)
PRIMES-TREMOVE	NMNL	CES	Driving profiles	--	BU	(E3MLab/ICCS, 2014)
ReMIND	-	Nested CES	-	-	H	(Pietzcker et al., 2010)
TRAVEL	NMNL	NMNL	-	-	BU	(Girod et al., 2012)
UKTCM	LM	E	-	-	BU	(Brand et al., 2012)

Notes: NMNL: nested multinomial logit model, MNL: multinomial logit model, LM: logit model, TTB: Standard budget and time budget constraints, TTI: travel time investment, E: elasticities, CES: constant elasticities of substitution.

Energy system models are usually technology-rich, thus allowing a precise description of the technical, environmental and economical characteristics of the technologies taken into consideration. Nonetheless, in determining the optimal shares to fulfil the travel service demand, traditionally these models only regard the life-cycle costs of the technology (actualized investment, operation and maintenance and fuel costs), disregarding that vehicle preferences are highly heterogeneous and based on many non-economic aspects. McCollum et al. (2016), recognising that low-carbon future transport scenarios have been explored so far without adequately considering any

behavioural aspect, have recently addressed the topic of behavioural realism of vehicle choice in IAMs. Four main methodologies were identified that are generally used to represent technology choice in a more behaviourally realistic way: (i) discrete choice models, (ii) constant elasticities of substitution, (iii) disutility costs and (iv) hurdle rates. A common trait of all these approaches is that they attempt to capture consumer behaviour when choosing a transport technology by including some non-monetary parameters that affect a consumer's decisions.

5.4.3.1 Discrete Choice Models

The most common approach observed in the literature to introduce technology choice is through discrete choice models. In this review, 5 models have been found to use this methodology, as shown in Table 5.3. Discrete choice models calculate the probability of an individual's choice from a finite set of alternatives. The selection of an alternative is determined through the principle of random utility maximisation, which assumes that individuals aim at maximising their utility when making a choice. Each alternative is characterised by means of both monetary and non-monetary parameters that influence people's choice.

As an example, Equation 5.1 illustrates the standard formula for a multinomial logit model (MNL) - a form of discrete choice modelling, which is used in the global transport model TRAVEL (Girod et al., 2012). This model calculates passenger transport shares and it is part of the energy model TIMER, which is in turn included in the wider IAM framework IMAGE (Van Sluisveld et al., 2016). Equation 5.1 calculates the fleet composition within a travel mode m at each time period t and region r for each vehicle v . The share of each alternative is calculated by comparing its cost with that of all the competing technologies within an exponential function that uses λ as a calibration factor.

$$Share_{r,v,t} = \frac{e^{(\lambda \times Cost_{r,v,t})}}{\sum_i e^{(\lambda \times Cost_{r,v,t})}} \quad (5.1)$$

In TRAVEL, the cost characterising each technology is calculated as shown in Equation 5.2.

$$Cost_{r,v,t} = \frac{AddTechCosts_{v,t} + EnergyCosts_{r,v,t} + NonEnergyCosts_{r,t}}{load_{r,t}} \quad (5.2)$$

The total cost is the sum of three addends:

- i. Investment into vehicles ($AddTechCosts_{v,t}$)
- ii. Energy costs accounting for vehicle efficiency and energy prices ($EnergyCosts_{r,v,t}$)
- iii. Non-energy costs related to vehicle purchase and maintenance, which simulate the increased willingness to pay, associated with higher levels of income ($NonEnergyCosts_{r,t}$)

In the hybrid model CIMS (Horne et al., 2005), an MNL model for vehicle choice is developed from stated preference surveys where respondents are asked to choose among four vehicle types defined by attributes such as capital costs, operating costs, fuel availability, express lane access, emissions and power. The gathered data serves to build the utility functions for each vehicle type j , as visible from Equation 5.3:

$$U_j = \vec{\beta}_j \times \vec{X}_j + ASC_j \quad (5.3)$$

The vector of attributes \vec{X}_j , is multiplied by the weighting coefficient vector $\vec{\beta}_j$, with the variable Alternative Substitution Constant ASC representing a specific constant for the alternative technology j . To represent this function in CIMS, market shares are computed according to Equation 5.4, where the utility functions are translated into capital costs (CC_j), operating costs (OC_j) and non-financial costs (travel time and comfort) per each mode i_j with a private discount rate r , and market heterogeneity exponent v :

$$Share_j = \frac{e^{U_j}}{\sum_j e^{U_j}} = \frac{\left[CC_j \times \frac{r}{1 - (1+r)^{-n}} + OC_j + i_j \right]^{-v}}{\sum_j \left[CC_j \times \frac{r}{1 - (1+r)^{-n}} + OC_j + i_j \right]^{-v}} \quad (5.4)$$

As demonstrated by the two examples reported above, discrete choice models are effective for introducing non-monetary parameters that affect individuals' decisions. Among the most commonly used intangible costs included in such models are technical risk of immature technologies, model availability, acceptance factors (to simulate accelerated market diffusion), density of recharging/refuelling infrastructure and range limitations.

Normally, the estimation of the model parameters and the calibration require data from a survey and a statistical analysis of the surveyed data. The time and cost of the data collection are a function of the number of alternatives to be included in the model. Discrete choice models find large-scale application in simulation programmes, where parameters statistically inferred from the survey simulate consumer behaviour. Conversely, optimization models are often based on linear

programming methods, hence model linking or a linearization procedure are required for the integration of the discrete choice models.

5.4.3.2 Constant elasticities of substitution

Another method of representing transport technology choice in the literature is that of using constant elasticities of substitution (CES). The CES between two input parameters of a utility function measure the constant percentage response of the relative marginal product of the two parameters to a percentage change of the proportion of the parameters. In the CGE model EPPA (Karplus et al., 2013), the original nesting structure described in (Paltsev et al., 2004) has been extended to include the possibility of substitution between conventional ICE vehicles and alternative fuelled vehicles (AFV), as shown in Figure 5.4.

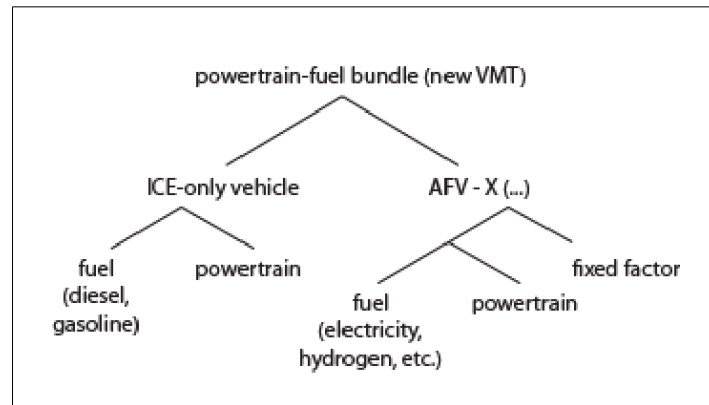


Figure 5.4: Representation of passenger vehicle choice in EPPA. Source: (Karplus et al., 2013)

CES regulate the choice between the transport categories, based on fuel costs, powertrain costs and a fixed factor, the latter accounting for different constraints on the adoption of alternative vehicles. Constraints on adoption include the gradual fleet turnover, dynamic changes in the relative cost of alternative technologies with respect to the existing technology, and fixed costs associated with reaching a stable production and obtaining wide market acceptance. The main advantage of CES is that capturing consumer behaviour in technology choice only requires the inclusion of additional input factors to capital and labour in the standard production functions. One problem associated with this method is that CES are generally the result of an educated guess or a literature review, since they cannot be calculated empirically. Moreover, they typically find application in top-down macroeconomic models and thus the integration in conventional energy models requires the adoption of soft linking or the use of a hybrid modelling approach.

5.4.3.3 Disutility Costs

The incorporation of disutility costs allows for considering the (often non-monetary) discomfort costs encountered by consumers when adopting a specific transport technology. Electric vehicles (EV) offer a common example, wherein the users could associate EVs with lack of refuelling infrastructure, range anxiety and scarce vehicle model variety. McCollum et al. (2012) provide a first example of the use of disutility costs in a linear programming model. In this case, technology choice is limited to fuel choice, including inconvenience costs for non-liquid fuels. A much more extensive use of disutility costs is offered by COCHIN-TIMES (Bunch et al., 2015) and MESSAGE-TRANSPORT (McCollum et al., 2016). The two studies apply the same methodology in different model frameworks: a linear programming tool (TIMES/MESSAGE) has been transformed to be able to replicate the output of MA³T, an MNL model designed to estimate the choice probabilities of an array of technologies for different consumer groups (Lin, 2015, Lin and Greene, 2010). By adding some extra features such as heterogeneity of population, disutility terms, and calibration parameters, the optimization framework is used as a “simulation-like” model. Heterogeneity is introduced to overcome the traditional concept of “mean representative decision-agent” (McCollum et al., 2014) and to take into account that distinct consumer groups are characterized by different preferences towards vehicle adoption and operation. In Bunch et al. (2015) and McCollum et al. (2016), consumers are differentiated along several dimensions: settlement pattern (urban, suburban and rural), attitude towards technology adoption (early adopter, early majority and late majority) and vehicle usage intensity (modest driver, average driver and frequent driver). Then, disutility costs are included to reflect that the different classes of transport users have varying preferences and comfort perceptions towards refuelling and recharging station accessibility, range anxiety and model availability.

While in MESSAGE-TRANSPORT disutility costs are homogeneous within each consumer group, the “unobserved consumer heterogeneity” is represented through distribution functions (called “clones”) in COCHIN-TIMES (Bunch et al., 2015), thus bringing the model results closer to the simulation model MA³T. This approach allows overcoming sharp technology penetration. However, the modelling complexity grows significantly, requiring high-level computational capacity.

Acknowledging that actors have varying sensitivities to cost differentials when making investment decisions, Li and Strachan (2016) include market heterogeneity and intangible costs/benefits in the dynamic stochastic socio-technical simulation model BLUE. This chapter recognises the combination

of transport users' heterogeneity and disutility costs as the most advanced and effective way to improve the behavioural realism of vehicle choice in optimization models.

5.4.3.4 Hurdle rates

Hurdle rates are higher discount factors associated with new or not fully commercial technologies. Hurdle rates account for the higher investment risk, uncertainty and imperfect knowledge perceived by the consumer, thus simulating the hesitancy to invest in a newer technology over an established technology (Mallah and Bansal, 2011). With respect to the transport system, the application of higher discount rates on less mature, more uncertain technologies is a traditional method to model vehicle choice. A simple approach consists of having technology-specific hurdle rates, while a more sophisticated method considers consumer-specific rates. In the model BLUE, Li and Strachan (2016) associate different hurdle rates to reflect actors' different attitudes towards investment risk. Horne et al. (2005) explicitly include the variable discount rate as part of the MNL formulation within the model CIMS, to simulate people's varying behaviour in vehicle purchasing decisions. The UKTCM model (Brand et al., 2012) distinguishes three main market segments for cars: private, fleet and business car buyers. Higher hurdle rates are associated to private vehicles to emphasize the higher total upfront costs confronted by the private consumer with respect to the fleet or business buyer. The allocation of variable hurdle rates to technology and consumer groups is a simple and generally applicable methodology in energy and transport models. The difficult calibration procedure and sole reliance on literature values for the determination of the discount rates represents a limitation for this approach.

5.4.3 Modal Choice

The endogenous inclusion of modal choice allows energy system models to determine the optimal pathway towards a policy target as a combination of technological and fuel switching, efficiency improvement and modal shifting, without relying on external assumptions on modal shares.

Transport simulation models such as LTM (Rich et al., 2010) have traditionally addressed modal choice using a 4-step model structure, including trip generation, trip distribution, mode choice and route assignment. In the third step, modal shares are normally computed via MNL or NMNL models using a large number of attributes describing the level of service of the alternative modes and the socio-economic composition of the population. Such an approach has some limitations: firstly, there is a need to conduct travel surveys to calibrate the model parameters (normally by means of log likelihood estimation). Secondly, the methodology is limited to simulation models – the logit model

structure based on exponential functions cannot be implemented in the linear optimization models commonly used for energy system analysis.

Modal choice proves to be a relevant behavioural feature to be included in 'E+T' models, being present in 12 out of the 14 models analysed. One of the main variables driving modal choice is travel time. Thus, an ongoing tendency to emphasize time importance in mode selection is that of including a constraint on the total travel time of the system: four of the models reviewed set a limit to the overall travel time within the linear optimization program. The main approaches identified for the representation of modal choice are: (i) Travel Time Budget (TTB), (ii) discrete choice models and (iii) constant elasticities of substitution.

5.4.3.1 Travel Time Budget (TTB)

The rationale behind the adoption of the concept of travel time budget (TTB) has been provided by Schäfer and Victor (2000), who claim that across different societies, geographical areas and income classes, people spend roughly the same amount of time per day travelling. Ahmed and Stopher (2014) provide an updated review of TTB studies, reporting a universal range for the TTB, equal to 60-90 minutes per person per day.

Models including the concept of TTB require changing the model structure to incorporate the parameter of speed, specified for every mode, eventually for every trip distance, and, within the optimization program, an upper bound on time consumption is set equal to the TTB.

Daly et al. (2014) apply the TTB concept to the TIMES models of Ireland and of California. This study aggregates all the mode-specific travel demands into a few "trans-modal" demand segments to allow a shift between modes, and subsequently uses a TTB to enable competition between fast but expensive technologies and cheap but slow technologies. With such a modelling approach, the optimal solution is not just the one that minimizes total system cost, but it also guarantees that the total system travel time does not exceed the TTB. The approach based on the TTB can be complemented by the concept of travel time investment (TTI), a proxy variable simulating the relationship between modal speed and infrastructure investment. Once TTI is incorporated in the model, it is possible to assess the influence of investing in the infrastructure of a certain mode on the market share of that mode. For instance, in Daly et al. (2014), TTI is used so that the model can invest endogenously in the infrastructure of modes, hence increasing their speed and reducing the travel time. Even if the model results shown by Daly et al. (2014) are sensitive to TTI, the use of this variable requires being refined. With the cost of TTI being critical to the determination of the modal

shares, additional efforts should be directed at determining a rigorous methodology to calibrate this variable. Determining a mode-specific stepwise cost curve, which includes speed reduction potentials from several infrastructure investments at different costs, could be a promising but also time-intensive approach.

Pye and Daly (2015) overcome some of the limitations and challenges of the TTI in the bottom-up optimization model ESME. They incorporate the approach by Daly et al. (2014), with some differences and they restrict the study to urban passenger transport and to trips shorter than 55 km. Two new constraints are introduced to better represent modal choice: the maximum level of modal shift potential and the rate of modal shift for each mode, which are determined by considering the historic trip distance profiles. Moreover, an adjustment factor on the TTB (equal to 0.95 hours/person/day) is used so that average urban speeds do not have to increase despite increasing demand. An important distinction from Daly et al. (2014) is that infrastructure is still considered, but only restricted to its cost, to give a more comprehensive picture of the cost of the modes. Infrastructure investments do not lead to improvements in travel time associated with different modes. However, the model must ensure that the sum of existing and new infrastructure is enough to accommodate the demand of mobility.

In the CGE model IMACLIM-R (Waisman et al., 2013) households derive utility from the consumption of goods and from the use of mobility services provided by four main transport modes (air, road, public and non-motorized). The value of the utility function is maximized, while subjected to two constraints:

- i. A standard budget constraint, which trades-off between transport-related expenditures and consumption of other goods.
- ii. A time budget constraint (TTB), which restricts the demand for transportation services purchased by households, considering that the speed of each mode is associated with the utilization rate of that mode (i.e. congestion effect). The induction effect of infrastructure deployment on mobility demand (TTI) is therefore addressed: an expansion of the infrastructure network makes modes faster, allowing households to travel more with equal time budget.

The main advantage of the TTB method lies in not requiring additional data but simply in introducing a general constraint to the problem. The concept of TTB has been criticized since it conflicts with

utility maximization, or with the principle that travel is a derived demand. Additionally, it has been argued that TTB is constant at an aggregate level while large differences may emerge as soon as one starts disaggregating populations in demographics, travel types and different spatial areas (Mokhtarian and Chen, 2004).

5.4.3.2 Discrete Choice Models

Within the 12 models reviewed which features modal choice representation, four adopt a discrete choice model to predict the choice probabilities of the different transport modes on the basis of travel time and travel cost, with GCAM (Kyle and Kim, 2011) accounting only for travel cost. In the hybrid model CIMS (Horne et al., 2005), an MNL model has been built from surveys in which respondents were asked to select among five modes (driving alone, carpooling, taking public transit, using a park and ride service, and walking or cycling), defined by the attribute travel time, cost, pick-up/drop-off time, walking/waiting time, number of transfers and bike route access. Survey data has been translated into parameters of the utility functions, used in CIMS through Equation 5.4.

In the bottom-up simulation model TRAVEL, an NMNL model calculates the mode shares based on a mode cost $Cost_{r,m,t}$ (for every region r , mode m and time t), where both travel cost and travel time are included:

$$Cost_{r,m,t} = k_{r,m,t} \times CostPerKm_{r,m,t} + TimeWeight_{r,m,t} \times TimeUse_{r,m,t} \quad (5.5)$$

Equation 5.5 presents two balancing parameters: $k_{r,m,t}$ is an adjustment factor for non-monetary differences in the total cost of different modes while $TimeWeight_{r,m,t}$ describes the relative importance of time and cost. This factor is endogenous to the model: if the total travel time per capita exceeds the TTB (assumed equal to 1.2 hours/person/day), the time factor $TimeUse_{r,m,t}$ is awarded a greater weighting (Girod et al., 2012).

In the model MESSAGE-TRANSPORT (McCollum et al., 2016), mode switching decisions are taken via a logit-based algorithm. The passenger travel demand projections split by mode are endogenously determined as the product of the total regional travel demand by the modal share for each mode, region and time, through MNL probabilities. These are expressed as the sum of fuel price, non-fuel price and a time element.

Advantages and disadvantages of discrete choice models in representing modal choice are the same as those for including technology choice previously discussed. In particular, it is interesting to notice that the concept of TTB can be easily integrated in this methodology, as e.g. in the model TRAVEL (Girod et al., 2012).

5.4.3.3 Constant elasticities of substitution

As with technology choice, modal choice can be modelled through CES. Examples of models using such an approach are EPPA (Karplus et al., 2013), PRIMES-TREMOVE (E3MLab/ICCS, 2014) and ReMIND (Pietzcker et al., 2010). In the latter study, the different transport modes are formulated in a nested CES structure, while at the lowest level of the tree diagram the technologies in each transport mode are represented with linear production functions. CES functions first regulate the substitution between freight and passenger transport, then between on-land, maritime and aviation, and finally between rail, truck, urban cars, intercity cars and bus. This nested structure was developed according to the level of linkage of the transport services and the ease of mode replacement. The model UKTCM (Brand et al., 2012) endogenously determines modal shares using elasticities: modal choice is modelled by linking through dynamic elasticities travel demand for each mode to vehicle ownership and operating costs, as well as to GDP and number of households. As previously discussed, the CES methodology can be best applied within a top-down framework and the values for the CES functions are typically estimated.

5.4.4 Driving Pattern

Five of the models analysed introduce the concept of driving pattern at different levels of detail. There are two main methodologies adopted: driving profiles and elasticities. Modelling driving pattern relates to account for the variable speed of modes and technologies, which can be associated to different levels of energy consumption and emissions. Intercity and urban transport have different impacts on energy use and CO₂ emitted (Schäfer, 2012). Fontaras et al. (2014) investigated the correlation between driving profiles and CO₂ emissions, determining that the highest emissions occur over urban conditions, reaching up to 290 g/km and 158 g/km for gasoline and diesel cars respectively, whereas the lowest occurred over extra-urban or rural conditions (averaging at 133 g/km and 107 g/km for the two fuel types examined).

Sectoral transport models (T) generally include a disaggregated geography of the transport system and calculate travel speed as an endogenous variable. These simulation models determine modal speed by allocating the endogenously generated transport demand split by modes to the road

network, considering the infrastructure capacity and congestion. Moreover, modal speed is reiterated to the modal choice module, which recalculates the modal shares accounting for the travel time of each mode.

In PRIMES-TREMOVE (E3MLab/ICCS, 2014), vehicle types are grouped into classes according to different driving profiles. COCHIN-TIMES (Bunch et al., 2015) and MESSAGE-TRANSPORT (McCollum et al., 2016) consider consumer heterogeneity, with yearly driven distance (a proxy for speed) as one classification criteria. IMACLIM-R (Waisman et al., 2013) contains a stylized representation of the relationship between infrastructure deployment (in terms of total vehicle capacity), modal demand and modal speed. In EPPA (Karplus et al., 2013), elasticities capture the relationship between fuel price, vehicle efficiency and mileage.

Disaggregating mode and vehicle speed at a greater detail would enable a better representation of fuel consumption and CO₂ emissions in the transport sector. While most energy system models already introduce the segmentation between urban and intercity transport (e.g., PRIMES-TREMOVE (E3MLab/ICCS, 2014)), thereby allocating different energy efficiencies and emission factors to the two alternatives, driving patterns have not been fully included yet. The reason for this lack of representation is most probably due to the modelling challenges and high computational time associated with great geographical/speed detail. In fact, a route assignment module is needed to represent speed endogenously, in turn requiring the description of the road network. Further modelling of driving patterns can be addressed through data collection from vehicles that track driving data e.g., speed and distance, harnessing the potential of big data analytics (Hawelka et al., 2014). This method can allow for the integration of data sets describing the real behaviour associated with driving profile, fuel use or time of use. On the other hand, a limitation lies in the uncertainty around the availability of such data.

5.4.5 New Mobility Trends

Among the models reviewed, only one deals with new mobility trends, specifically addressing carpooling. As introduced in Section 5.4.1, new mobility trends refer also to increasingly recurring phenomena like car sharing systems, autonomous vehicles and optional transport abdication connected to teleworking.

CIMS regards carpooling as an additional mode, selected among the various alternatives based on MNL probabilities (Horne et al., 2005). In this way, the ratio between car drivers and car passengers

is determined by choice probabilities considering capital costs, fuel costs, weighted average travel time and some intangible costs reflecting the perceived benefits or drawbacks of using a certain technology.

A possible option for modelling carpooling is to account for vehicle occupancy factor by analysing the relationship of this variable with population characteristics like age, gender, income and travel type. The potential of adopting a car sharing system for reducing the environmental impact of the road transport sector has been also assessed through a case study in the city of Montreal (Sioui et al., 2013): the results show that there is a 25% difference in the modal share of car use between a person with full access to a car and a high-frequency user of the car sharing with no car.

Autonomous vehicles may affect energy consumptions and emissions in a broad spectrum of ways, both positive and negative. Wadud et al. (2016) explore the net effects of automation on emissions, considering phenomena like platooning, eco-driving, congestion, improved crash avoidance, travel cost reduction, and new user groups. Results show that many potential energy-reduction benefits may be realized through partial automation, while the major downside risks appear more likely at full automation. However, robust conclusions cannot be drawn, as there is a high level of uncertainty on the evolution of the phenomena. Different prospects of users' behaviour towards this technology could be incorporated in E+T models, as to support the investigation on the mitigation potential of autonomous vehicles.

Generally, new mobility trends do not find a sufficient representation in the models reviewed. Nonetheless, there are growing efforts in the international energy and transport modelling community towards a better understanding of the concept of Mobility as a Service (MaaS) and the impact it may have on the future transport system (Kamargianni et al., 2016).

5.5 Discussion

All models share the common trait of attempting to represent some aspects of a system as accurately as possible. Despite this, the representation of behaviour in integrated energy and transport models, or lack thereof, has lead towards potentially misguided analyses. From a policy perspective, improving the modelling of transport behaviour represents a step forward in supporting the analysis and definition of more targeted and effective transport and energy measures. The increased level of detail in the representation of the transport sector allows studying the cost and impact of specific policies, possibly diversified for each transport technology, mode or consumer

group. Regulatory and market-based strategies with a clear and quantitative definition of their economic effects and temporal applications could be tested through the improved optimization and simulation models. On the other hand, softer measures, typically informational or voluntary-based programs (Richter et al., 2011), include a more descriptive specification and are therefore less applicable to these models.

When a model contains an advanced incorporation of transport *technology choice*, costs and other non-monetary parameters are used to characterize the vehicle technologies. Additionally, the segmentation of consumers according to their attitude towards car purchase and use allows addressing tailored strategies for supporting the transition to a more sustainable transportation system. For instance, the model can test the effectiveness of subsidies incentivizing the purchase of electric vehicles, now considering a heterogeneous group of potential vehicle purchasers. The system cost of the introduction of “feebate” schemes, i.e., a combination of rebates awarded to purchasers of low-carbon emission vehicles and fees charged to purchasers of less efficient vehicles (IPCC, 2014b), could be computed as well. Moreover, models could analyse the impact of public investments in the refuelling infrastructure of electricity and low-carbon fuels on the adoption of new car technologies. The possibility of endogenously determining the market shares of the *modal choice* enhances the analysis of a large set of measures promoting the shift from private to a more efficient mode of transport: national and regional strategies targeting investments in public transport infrastructure (e.g. dedicated bus lanes), decrease in public transport cost, fuel and vehicle purchase taxes, road-pricing, vehicle restrictions and parking reforms in cities.

Although few of the models reviewed include a comprehensive incorporation of *driving patterns*, some of them attempt to model the relationship between infrastructure investment and mode market shares, while others segment vehicle users into different groups according to their driving profile. These models can aid the definition of respectively strategies for improving the urban traffic management (e.g. speed limits) and eco-driving programmes affecting driving behaviour. Finally, the inclusion of *new mobility trends* (or Maas) could allow the assessment of strategies promoting vehicle sharing services and the spread of carpooling adoption, along with the impact of transport demand reduction as a consequence of teleworking (Cohen-Blankshtain and Rotem-Mindali, 2016).

5.6 Conclusion and Recommendations

This chapter analysed twenty-seven integrated energy and transport models and created a taxonomy for these various model types.⁶ This chapter reviewed the methodologies adopted for introducing behavioural features related to consumer purchase, adoption and use of transport technologies with the purpose of addressing two questions: (i) how should transport and energy models be structured to allow an effective inclusion of behaviour and (ii) what key attributes and parameters should be introduced to represent transport-related consumer choices in an integrated energy and transport model. Relating to the former question, the chapter concludes that there are three common approaches for structuring a model to improve the representation of behaviour - top-down, bottom-up, and hybrid structures - each of which have advantages and disadvantages depending on the scope and purpose of the model analysis. Nonetheless, soft-linking and novel approaches recently developed (see Section 5.4) emphasise a bottom-up model structure as the most flexible and promising method. Concerning the latter question, this review identified technology choice, modal choice, driving patterns and new mobility trends as the key features to correctly depict transport behaviour in integrated energy and transport models (E+T). Furthermore, heterogeneity, travel time budgets and driving profiles are recommended as the key attributes and parameters to be introduced in 'E+T' models to represent such behavioural features.

5.5.1 Structure

Top-down (TD) models examine the entire economic system in a detailed way and constitute a valid tool to simulate the economic mechanisms that regulate technology substitution. They can be used to endogenize modal or vehicle choice and to answer research questions concerning the relationship between modal/technological demands and fuel/electricity prices. Nonetheless, having the economic sector as the core and focus of the model, TD models may fail at including a comprehensive set of fuels, vehicle technologies and modes. The attributes characterising the different transport alternatives are often rendered to a low level of accuracy and TD models are less capable at directly capturing the effect of changes in efficiency, mileage and occupancy factors, relative to BU models. Further efforts are required to bring such models to a technologically rich format, as done by Karplus et al. (2013).

⁶ Sectoral energy models (E), energy models partially including the transport sector (E+), highly integrated energy and transport system models (E+T), transport models partially including the energy sector (T+), and sectoral transport models (T) (see Section 5.3)

On the contrary, *bottom-up (BU)* models more suitably analyse the effect on the overall energy system of certain exogenously imposed modal/technology shares. As long as vehicle market shares are exogenous assumptions, pure BU models prove to be a valid policy analysis tool. Inversely, to endogenously determine behaviourally realistic market shares, the BU framework needs to be upgraded by adding new variables or by linking it with external socio-economic transport-focused models, of the ‘T’ or ‘T+’ types.

Hybrid models join and harness the advantages of BU and TD frameworks, thus proving more capable at capturing many of the behavioural features discussed. They are valuable at answering research questions investigating both the energy sector and the surrounding economy. However, the structure of this class of models is inherently more complex when compared to pure BU or TD models, potentially creating issues with computation. The model comes as a “single-package”, not separable into the TD and BU components, thus limiting the flexibility of its use.

Of the three structures outlined above, this review regards BU models as the most promising approach to include a representation of behaviour in E+T models. The benefit of representing behaviourally realistic choices directly within an energy system model is manifold. Firstly, these improved BU models allow for energy system-wide considerations. Secondly, they support in the understanding of the future reciprocal implications of decisions taken in the transport and energy systems. Thirdly, a much wider variety of policies can be assessed through the E+T framework, as further discussed in Section 5.6. Because BU optimization models do not originally represent behaviour, either they need to be soft-linked with an external transport simulation model which has a predefined representation of behaviour, and uses a complementary mathematical method, or their structure needs to be adjusted to accommodate the new behavioural features. The former approach makes the model flexible - whenever the analysis is not purely transport focused, the energy system model can run in standalone mode with a simplified representation of the transport sector. The latter approach is further discussed in Section 5.5.2.

5.5.2 Parameterisation

Technology and behaviour measures have been identified as critical measures in addressing transport CO₂ emissions, in particular, avoiding, shifting, and improving (IEA, 2012a). For this reason, this chapter aimed at identifying the most suitable method(s) of representing technology choice (improving), modal shifting (shifting) and both driving patterns and new mobility trends (avoiding) in ‘E+T’ models.

Including heterogeneity was regarded as the best means of improving the representation of *transport technology* choice. Traditional BU energy system models assume homogeneous consumers taking perfectly rational decisions. Introducing heterogeneous decision makers is a precondition for incorporating behaviour in ‘E+T’ models. Heterogeneous transport users have different preferences, resulting in a wide portfolio of technologies chosen, each one optimal for a specific consumer group. When deciding the number of dimensions along which consumers are split and the number of behavioural features to consider, a compromise between model complexity and completeness needs to be made. An ideal representation of transport behaviour within an ‘E+T’ model would involve representing all consumers within the region in question, yet the computation power required for this level of detail renders this method incredibly onerous. To avoid intractability or excessive complexity of the model, efforts should be addressed towards determining the minimum number of dimensions and subgroups necessary and sufficient to distinguish the main consumer groups in an exhaustive way.

Of all approaches reviewed regarding *modal choice* representation, travel time budget (TTB) is recommended as the best method of modelling this feature within BU models. It can be introduced by adopting literature values (Schäfer and Victor, 2000) or eventually more region-specific TTBs, available from national travel surveys. Moreover, the concept can be easily incorporated in the model, requiring only the definition of modal speed and the setting of a constraint (as in Daly et al. (2014) and Pye and Daly (2015)). An interesting area for future work would be to adapt the methodology proposed by McCollum et al. (2016) and Bunch et al. (2015) to cover modal choice in BU optimization models – to provide reliable modal shares and calibrate the intangible costs suitably, the energy system model requires drawing data from a detailed support model (e.g., of the ‘T’ type) that incorporates modal choice.

There is a need to model *driving patterns* at a detailed geographical level to accurately account for fuel consumption and emission factors from vehicles, which strongly depend on the driving performances. The relationship between modal speed and infrastructure could be incorporated in the integrated energy and transport model as was carried out in the model IMACCLIM-R (Waisman et al., 2013). Another possible method consists in adapting the approach by Ramea et al. (2016), where the congestion level, and thus the modal speed and emission factors, is determined in an iterative way as a function of the infrastructure capacity.

Modelling *new mobility trends* offers the opportunity to explore and unlock their potential in contributing to more sustainable transportation systems (Wadud et al., 2016, Grischkat et al., 2014). Car sharing services can possibly be modelled by introducing a new car technology type characterized by a higher mileage per year. Carpooling can be incorporated in integrated energy and transport models by considering a lower car-ownership level and higher occupancy factors.

Chapter 6

The Cost of Electrifying Private Transport – Evidence from an Empirical Consumer Choice Model of Ireland and Denmark

Abstract

There is a growing consensus that moving to a low carbon future within the transport sector will require a substantial shift away from fossil fuels towards more sustainable means of transport. A particular emphasis has been given to battery electric vehicles (BEV) and plug in hybrid electric vehicles (PHEV), with many nations investing in improving their charging infrastructure and incentivising electric vehicle purchasing through offering grant schemes and tax relief to consumers. Despite these incentives, the uptake of BEVs and PHEVs has been low, while some countries, such as Ireland and Denmark, are in the process of removing the tax relief currently in place. This initial retraction has been met with a fall in the sales of BEVs and PHEVs, which is expected to continue decreasing as these incentives are further reduced. This study develops a socio-economic consumer choice model of the private transport sector based off national empirical data for Ireland and Denmark to analyse the long-term effects of these subsidy retractions, and to further analyse the policy measures and associated cost of moving towards a low-carbon private transport sector.¹

¹ Chapter based on the submitted journal article: Mulholland, E., Tattini, J., Ramea, K., Yang, C., Ó Gallachoir, B. P., “The cost of electrifying transport – evidence from an empirical consumer choice model of Ireland and Denmark”, *Transportation Research Part D: Transport and the Environment*, Submitted in August 2017

6.1 Introduction & Motivation

There is a growing consensus that moving to a low carbon future within the transport sector will require a significant shift from its current state, whereby conventional fossil fuelled internal combustion engines (ICE) dominate the market, to sustainable means of transportation (IPCC, 2014b). This shift is considerable, as it requires a fundamental change in both the fuel type and the vehicle technology of the transportation sector. Considering private transport, which constitutes 42% of global well-to-wheel (WTW) transport related emissions (IEA, 2017a), this shift will involve multiple agents. *Fuel suppliers* may provide emission reductions through altering the composition of the fuels offered to consumers vis-à-vis the blending of bio-ethanol and bio-diesel with gasoline and diesel respectively or providing new fuels (e.g. CNG, LPG or H₂). *Automobile manufacturers* may provide efficiency improvements and innovative technologies capable of reducing downstream vehicle emissions. *Governing bodies* may impose regulations through fuel standards and minimal requirements for the performance of new vehicles while also incentivising the sale of low emitting vehicles. Finally, *consumers* – arguably the most vital agent in private transportation – choose which vehicle technology to purchase.

The potential emission reductions available from these former two supply agents are constrained by current technological limitations. European fuel standards, for example, mandate a maximum blend of conventional biofuel with petrol and diesel ICEs at 5% (CEN, 2008) and 7% (CEN, 2009) respectively (previously discussed in Chapter 4), while the long-term efficiency improvement potential available to conventional ICEs has been identified as 28% and 33% for a spark ignition and compression ignition engine respectively, relative to a 2005 spark ignition engine (IEA, 2008).² While these measures offer potential short-term and medium-term solutions to meeting national emissions reduction targets, increasing the penetration of low-carbon alternative fuelled vehicles (AFV) will be imperative in advancing towards carbon reductions capable of adhering to a future with a global temperature rise limited to less than 2°C (IEA, 2017a). Despite this necessity, the uptake of non-ICE vehicles has been very low, suggesting that numerous barriers prevent a significant deployment of these vehicles. Moreover, the price of removing these barriers can be rather costly in the short-term, with little certainty surrounding effectiveness.

² These efficiency improvements are gained through a combination of reducing engine friction, starter-alternator components, variable valve lift and timing, advanced cooling circuits, electric water pumps, and transmission improvements

To quantify these barriers, the many costs pertaining to vehicle consumer choice can be loosely grouped as *tangible costs* and *intangible costs*. *Tangible costs* consist of the actual costs the consumer is faced with when choosing a vehicle, e.g., investment cost, operational and maintenance costs (O&M), taxation, and fuel costs. The nature of these costs allows for a quantifiable monetary figure to be associated with each factor. *Intangible costs*, however, represent the many non-monetary perceived costs the consumer faces when using a vehicle, e.g., inconvenience due to low vehicle range and limited refuelling infrastructure, acceptance of new and uncertain technologies, fewer options about the characteristics of the vehicle (such as number of doors, colours available, size, etc.) These costs are generally difficult to quantify, as their perception changes for different consumer groups. Nonetheless, for regulators it is important to monetise these intangible costs in order to elaborate effective strategies to remove these barriers.

This study presents a methodology which monetises these intangible costs using empirical data from national sources to create a dynamic vehicle consumer choice model of Ireland and Denmark. This consumer choice model is linked to a sectoral simulation model of the private car sector (the CarSTOCK model, introduced in Chapter 4 and extended to represent Denmark in this chapter) to indicate the cost and potential effectiveness of policy interventions in the form of WTW carbon dioxide (CO₂) emission savings. Ireland and Denmark have been chosen as a case study as both are in the process of removing subsidies for battery electric vehicles (BEV) and plug in hybrid electric vehicles (PHEV) by the turn of the decade (see Figure 6.1 for a detailed breakdown) (Department of Finance, 2017), (Skatteministeriet, 2015). In the case of Denmark, the initial retraction of the VRT subsidy for BEVs and PHEVs in 2016 was met with a drop in combined BEV and PHEV sales of 42% relative to the previous year (EEA, 2017). These subsidy withdrawals have been announced despite both countries identifying the necessity of electrifying transport in moving towards a low carbon future, (DECLG, 2016, The Ministry of Climate Energy and Building, 2013).

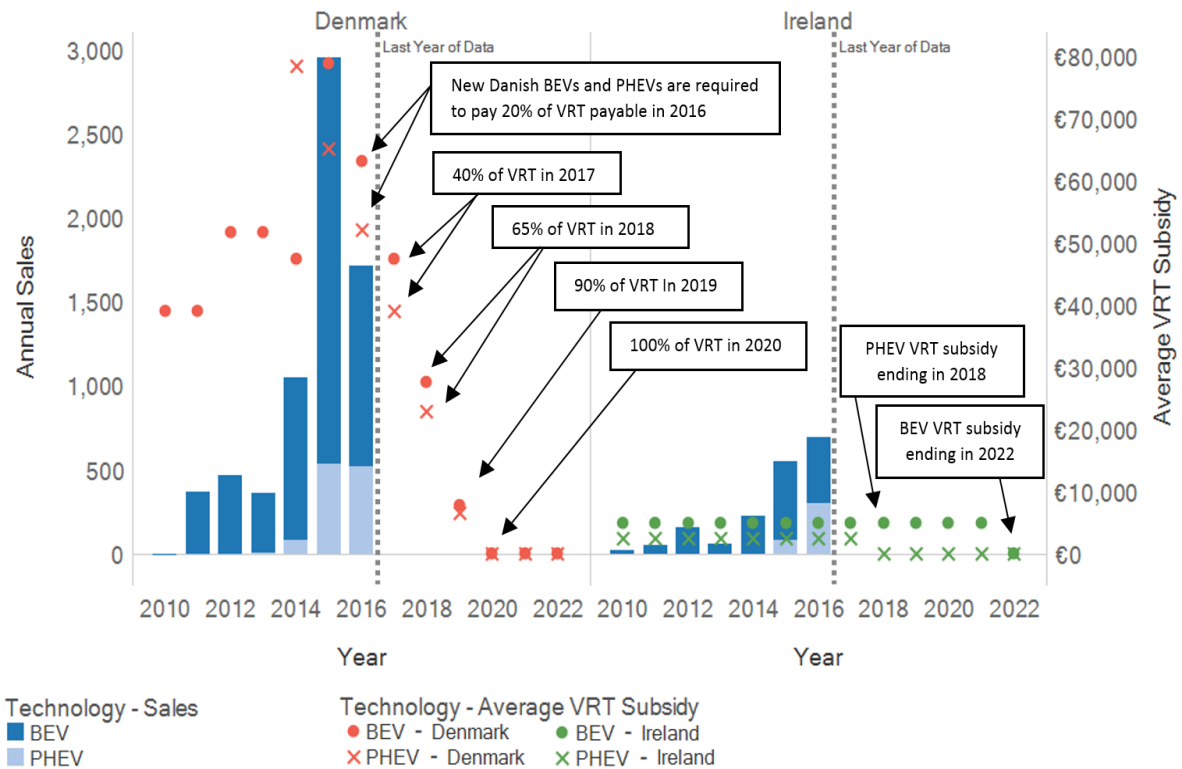


Figure 6.1: Sales of BEVs and PHEVs in Denmark and Ireland and corresponding average VRT relief³ available

The purpose of this study is threefold; (i) to contribute to the current body of scientific literature surrounding the area of modelling consumer choice within the private transport sector through use of revealed preference data, (ii) to determine the long-term effect of revoking tax relief for BEVs and PHEVs in Ireland and Denmark on stock composition and emissions, and (iii) to determine the cost and effectiveness of implementing further governmental level policy measures which incentivise BEV and PHEV purchasing. In keeping with the order of these points of purpose, this chapter is structured similarly. Section 6.2 discusses the value of modelling consumer choice within the transport sector, Section 6.3 describes the model inputs, structure and operability, Section 6.4 presents the impact of varying the market determinants mentioned above and Section 6.5 concludes.

6.2 The Importance of Modelling Consumer Choice

There is a growing body of literature which emphasises the necessity of moving away from models driven solely by economic parameters by including attributes related to consumer behaviour, thus enabling a more accurate representation of consumer choice (Mabit, 2014, Garcia-Sierra et al.,

³ The Danish VRT system is based on the cost of the vehicle (105% of the first 81,700 DKK (€10,800) and 180% of the remainder) with further slight subsidies for all vehicles dependant on fuel efficiency. The VRT relief for BEVs and PHEVs was calculated from the annual sales weighted average cost of the vehicle, while the projected VRT relief was calculated by holding the vehicle cost constant from 2015 onward and decreasing the VRT relief according to the text in Figure 6.1

2015). This is imperative when analysing how to facilitate the shift towards sustainable mobility: without differentiating heterogeneous consumer groups and capturing the barriers that oppose the uptake of AFVs for these groups, both governing bodies and modellers alike are liable to an over-simplified representation of the market which they are attempting to alter. This over-simplified representation in turn may lead to unrealistic scenarios for the modeller and ineffective policies for the policy maker.

In an ideal consumer choice model, each agent would have a singular representation, with every applicable behavioural attribute accounted for to determine the utility of each vehicle available to purchase. In this way, the least-cost process of improving AFV utility for each consumer could be addressed. Of course, the scope of such an ideal representation would not only require a substantial level of computing power to model, but also an extensive data set to drive achievable through a comprehensive stated preference survey (SPS). Thus, while aiming at developing a representative and valid model, there is a need to limit both the number of consumer segments and applicable behaviour attributes.

6.2.1 Consumer Segments

Behaviour economics and psychology play a central role in breaking down the complex nature of the rationale behind consumer behaviour into comprehensible segments (Mattauch et al., 2016). These segments can be defined by many different attributes, e.g., demography, geography, and driving profiles. While consumers can be defined by a wide-ranging array of these segments branches, it is necessary to identify those which can be accurately represented (for the modeller) and those which can act as a policy lever (for the policy maker). Numerous studies have been dedicated to identifying these important behaviour attributes influencing consumer choice of private vehicles. For example, (Wilson et al., 2014) created a synthesis of 16 peer-reviewed articles which use discrete choice experiments informed by SPSs in examining preferences for AFVs. The studies analysed had a wide geographical range with findings that socio-demographic characteristics - particularly age, gender, and education - influence choices. These characteristics can be used to segment consumers in adopter categories. Roger's classification of technology adopter types is a common framework for segmenting consumers, whereby the market is split into different classes of innovators (Rogers Everett, 1995). Combined with the findings of (Wilson et al., 2014), Roger's diffusion of innovation theory provides a means of differentiating the innovators of a market, who would be the likely early investors in AFVs, from the laggards, who would be more reluctant from investing in new technologies. Creating these segments allows the modeller to vary behaviour attributes, e.g., range

anxiety, for different portions of the market and for the policy maker to target consumer groups more effectively. Further examples of transport consumer choice models which segment the market by varying levels of innovations can be found in Brand et al. (2017), (McCollum et al., 2016), and (Bunch et al., 2015).

6.2.2 Behaviour Attributes

As with consumer segments, the number of behaviour attributes which affect private vehicle-related purchasing decisions are wide ranging and are commonly left unrepresented in traditional energy system models. For energy systems models that wish to include heterogeneous decision agents, it is extremely difficult to represent all relevant behaviour attributes related to vehicle purchasing (McCollum et al., 2016), forcing these models to limit the inclusion of these attributes to those relevant for a specific research question.

This study draws upon the findings from the MA³T model, a nested multinomial logit (MNL) choice model developed by Oak Ridge National Laboratory, which uses the US National Household Travel Survey to determine the disutility costs (the non-monetary adverse effects faced by the consumer when purchasing a vehicle) associated with many of these attributes. Studies from this model determined vehicle model availability, risk related disutility, range anxiety, and refuelling/recharging infrastructure availability to be amongst the greatest contributors (Lin and Greene, 2011). This is broadly in agreement with the findings of both (Wilson et al., 2014) and (Sierzchula et al., 2014), and thus stands as the extent of behaviour attributes examined within this study.

(i) *Model availability and risk related Disutility*

There are a wide range of vehicle characteristics which may influence a consumer's preference when purchasing a vehicle, e.g., car brand/model, vehicle cabin (sedan, hatch back, station wagon), engine type, car weight, car power, transmission system, number of doors, colour, alloy frame, etc.

Although each of these characteristics can be individually classified as a behaviour attribute, they may be grouped under the overarching theme of model availability. Automobile manufacturers, in general, aim to provide a wide array of vehicles which fulfil the individual preferences of as many consumer segments as possible. Thus, the magnitude of the disutility cost associated with model availability for a vehicle class rises as the number of models available fall, and vice versa.

Prior to achieving a substantial market share, new technologies are generally met with a varying level of aversion towards adoption, dependent on the consumer segment. The early adopters, in accordance with the theory pertaining to the diffusion of innovations, perceive this risk to be

negative as the novelty of a new technology is appealing to this consumer group. On the other hand, their laggards' counterpart perceive it to be positive due to unfamiliarity. The disutility cost associated to this attribute is only relevant to AFVs as conventional ICEs are now widely accepted across all consumer segments. As the adoption of a particular AFV becomes widespread in a certain market, the risk related disutility converges on zero.

(ii) *Range Anxiety and Refuelling Infrastructure*

There is a disutility cost associated with both range anxiety - a term used to encompass the perceived penalty associated with a failure to meet a daily travel demand due to limited battery range – and limited availability of refuelling infrastructure. Both of these disutility costs vary dependant on the travel profile of a consumer, while the magnitude of these costs varies based on the efficiency and range of a vehicle, alongside the recharging/refuelling infrastructure availability for the fuel used. Range anxiety has an associated penalty perceived by the consumer, which varies over time as a technology becomes more widespread. The disutility cost of range anxiety is faced only by BEVs, as the consumer acceptance of ICEs and PHEVs prevents any associated risk with this attribute. Refuelling infrastructure represents a disutility faced by all vehicle types, although the strong presence of petrol and diesel refuelling stations globally renders this cost to be minimal for ICEs.

6.3 Methodological Approach

The approach employed by this study develops a consumer choice model of the private transport sector for Denmark and Ireland and links the outputs of this model to a sectoral simulation model of the private car sector to generate the resulting change stock and WTW CO₂ emissions due to governmental policies. Both models use the base year of 2015. This work has been largely inspired by previous discrete consumer choice models (McCollum et al., 2016, Bunch et al., 2015), and expands on these pieces of work through the integration of a sectoral simulation model and the reliance on publicly available data related to the private vehicle market.

The consumer choice model embodies the tangible costs faced by the consumer along with a monetised representation of the intangible costs related to model availability, risk related disutility, range anxiety, and refuelling infrastructure. These intangible costs are monetised via publicly available empirical data, where possible, to provide a method which is replicable for other countries with similar data availability. This study differs from most consumer choice models to date by relying

on revealed preference of consumers shown through publicly available empirical data rather than stated preference, as was the case in Bunch et al. (2015) and Hackbarth and Madlener (2013).

This consumer choice model computes only the private vehicle market shares, and cannot determine the impact of policy measures on aggregate stock or emissions. To account for this, the CarSTOCK model is linked with the consumer choice model. The CarSTOCK model is a bottom-up techno-economic model which uses the market shares from the socio-economic consumer choice model, in tandem with a technically detailed representation of the transport sector, to provide a full representative of the breakdown of stock, energy consumption, activity, and WTW CO₂ emissions in both Ireland and Denmark, thus determining the net effect of policy measures.

Scenario development is finally carried out within the consumer choice model, whereby policy specific scenarios pertaining to changes in vehicle registration tax (VRT), value added tax (VAT), annual motor tax (AMT), market regulation, and fuel costs are created, resulting in detailed market shares of 15 private vehicle technologies. These market shares are then entered into the CarSTOCK models for Ireland and Denmark to simulate the effect these policy measures would have on long-term stock, WTW CO₂ emissions, and energy consumption. This full method is summarised in Figure 6.2.

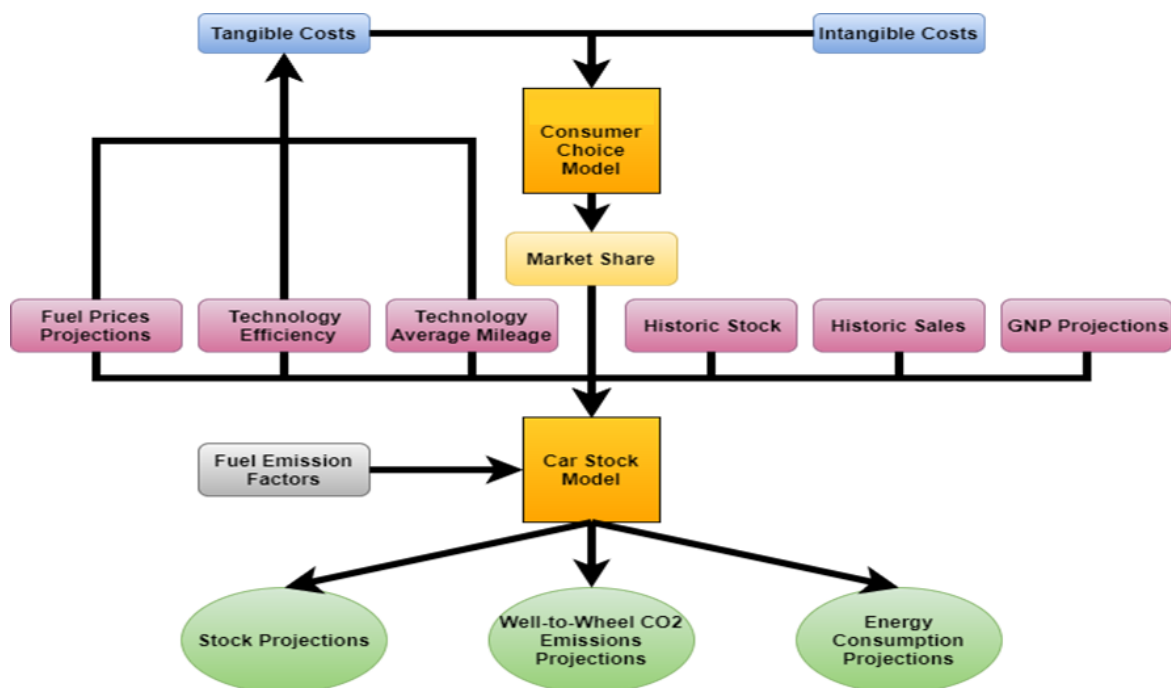


Figure 6.2: Multi-model methodology

6.3.1 Consumer Choice Model

The consumer choice model used in this study is a socio-economic model built to estimate the effect of various policy measures on the private vehicle market. In both Ireland and Denmark this market is heterogeneous, so the segmentation of the market is critical to appropriate the variance in intangible costs accurately. Based on the review carried out in Section 6.2.1., the private vehicle consumer market is split into 18 segments divided geographically (urban/rural), by driving profile (Modest Driver, Average Driver, Frequent Driver) and by class of innovation (Early Adopter, Early Majority, Late Majority), as shown in Figure 6.3.

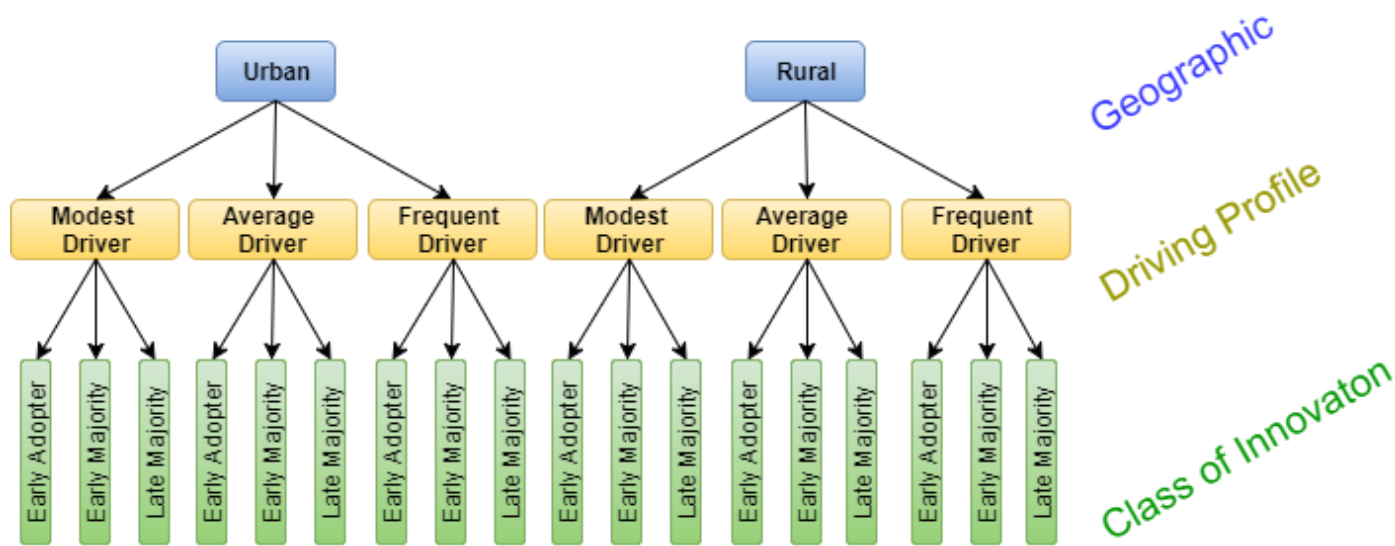


Figure 6.3: Consumer choice model consumer segmentation

The geographical split is made in accordance with the latest EU urban-rural typology (Eurostat, 2014). The driving profile segmentation is split by consumers with an average annual mileage of 15,000km (modest driver), 20,000km (average driver) and 25,000km (frequent driver). Vehicle technologies were categorised to correspond with these driving profiles. Annual mileages were found to vary in both Ireland and Denmark dependent on vehicle engine size (see Table 6.1). Therefore, the four ICE technologies considered (petrol, diesel, hybrid, PHEV) were split into 3 further bands: small (<1,300cc for Ireland, <1,400cc for Denmark), medium (1,300cc-1,700cc for Ireland, 1,400cc – 2,000cc for Denmark), and large (>1,700cc for Ireland, >2,000cc for Denmark). The variance in bands were chosen to correspond to the driving profiles defined above. BEVs were also split into 3 bands based off their range (<125km, 125km – 175km, and >175km).

Table 6.1: Vehicle categories and classifications⁴

Vehicle Classification	Ireland		Denmark	
	Engine Size	Mileage (km/yr)	Engine Size	Mileage (km/yr)
Small	<1,300cc	14,102	<1,400cc	14,257
Medium	1,300cc -	19,257	1,400cc -	18,263
	1,700cc		2,000cc	
Large	>1,700cc	24,339	>2,000cc	22,714

The classes of innovation are split by age groups, based on the synthesis of findings from the review of SPSs in Wilson et al. (2014) which found that: “Respondent age was consistently reported as significant in AFV choice with younger people more likely to choose different types of gas, electric, biofuel, and fuel cell vehicles”. The age groups were chosen from the census population data of number of people with eligibility to drive and split geographically into the groups of <35 years (early adopter), 35 – 65 years (early majority) and >65 years (late majority), as the share of these groups relative to the driving population were found to roughly correspond with the market share of Roger’s innovation classes (Rogers Everett, 1995).

The 15 private vehicle technologies were placed in direct competition with each other within each relevant consumer segment, e.g., small petrol, small diesel, small hybrid, small PHEV and all BEVs were in direct competition within each modest driver segment. The market share is calculated based off the perceived life cycle costs (LCC) of a vehicle using Equations 6.1 and 6.2, which are drawn from the CIMS hybrid energy-economy model, (Jaccard, 2009) (see Appendix C).

$$MS_{k,s} = \frac{(LCC_{j,s})^{-v_a}}{\sum_{k=1}^K (LCC_{k,s})^{-v_a}} \quad (6.1)$$

$$LCC_{j,s} = \left(CC_{j,s} * \frac{r}{1 + (1 + r)^{-n}} + MC_{j,s} + FC_{j,s} + IC_{j,s} \right) \quad (6.2)$$

Market share (*MS*) is calculated for each technology (*j*), and segment (*s*) in year *n* accounting for tangible costs - capital costs (*CC*) (which includes purchasing related taxes), maintenance costs (*MC*), and fuel costs (*FC*) - and intangible costs (*IC*) - which is a combination of costs associated with the

⁴ Data for Ireland for these classifications were collected from the National Car Test, which all private cars beyond four years old are obliged to take, and whereby the annual mileage of each tested vehicle is recorded. Data for Denmark has been obtained combining the inspection data of the Danish Road Directorate with the Administrative Car Register

behaviour attributes defined in Section 6.2.2. Capital costs are annualised, in order to be made comparable with all other costs, through the use of a discount factor r with a value of 25.7%, which is the current discount rate for private cars adopted in the full CIMS-US model. This falls within the range of vehicle related discount factors used from the review of similar values within literature carried out by (Train, 1985). Admittedly, this represents US data which may differ from European data, although an SPS could be used to generate a European specific discount factor although was out of the scope of this study. A variance parameter (v_a) is introduced to enable a more behaviourally realistic allotment of market shares to the vehicle technologies. A high value of v_a represents a ‘winner takes all’ phenomenon whereby the lowest costing vehicle takes close to all of vehicle sales within a segment. On the contrary, a low value of v_a distributes sales more evenly regardless of differences in life-cycle costs, where a value of 0 produces a completely even share across all technologies. The CIMS model uses a variance value of 15 calculated using a method of ordinary least squares to correspond an SPS with the scale of the model (Rivers and Jaccard, 2005).

The remainder of this section discusses the sources of tangible costs, intangible costs, and provides a detailed modelling framework for the stock simulation model used.

6.3.1.1 Tangible Costs

The total tangible costs – capital cost, operation and maintenance cost and fuel cost - were collected from a variety of publicly available national statistic sources for both countries. Historical data for each cost component were available for Ireland over the period 2004 – 2015 and in Denmark over the period from 1986 – 2015 for all data with the exception of purchasing cost, which was only available at a technology specific level until 2008. A summary of all cost components, corresponding value ranges, and sources are presented in Table 6.2, with a graphical summary of all tangible costs for the 15 technologies within the scope of this study shown in Figure 6.4.

Table 6.2: List of tangible costs in Ireland and Denmark, 2015

Tangible Cost Variable	Cost Components	Ireland Value Range (2015€)	Ireland Sources	Denmark Value range (2015€)	Denmark Sources
Capital Cost	Purchasing Cost excluding taxes	€11,512 - €50,054	(SIMI, 2017)	€7,368 - €54,126	(FDM, 2017a)
	VRT	Based on CO ₂ emissions (14% - 36% of the Open Market Selling Price)	(ACEA, 2017)	105% of first €10,800 of the dealer's sales price and 180%* of the remainder, with reductions based on fuel economy and traffic safety equipment	(ACEA, 2016)
	VAT	23% of basic price of vehicle before VRT	(Revenue, 2015)	25% of the dutiable value at the time of their acquisition in new condition	(ACEA, 2017)
	Subsidy	€7,500 - €10,000	(Department of Finance, 2017)	€59,003 - €90,785	(Skatteministeriet, 2015)
Operation and Maintenance Cost	Annual Motor Tax	Based on CO ₂ emissions (€120 – €2,350/yr)	(ACEA, 2017)	Based on fuel economy (€34 – €4,186/yr)	(Skatteministeriet, 2017)
	Insurance	€1,003 - €1,757	(AA, 2015)	€981 – €1,295	(FDM, 2017b)
Fuel Cost	Fuel Price	€1.53/ltr – Petrol €1.45/ltr – Diesel €0.10/kWh - Electricity	(AA, 2017)	€1.50/ltr – Petrol €1.27/ltr – Diesel €0.23/kWh - Electricity	(Country Economy, 2017)
	Vehicle Efficiency	6.66 – 0.91 l/100km	(Dineen et al., 2014)	8.48 – 0.91 l/100km	(FDM, 2017a)

*This value changed to 150% in 2016 (ACEA, 2017)

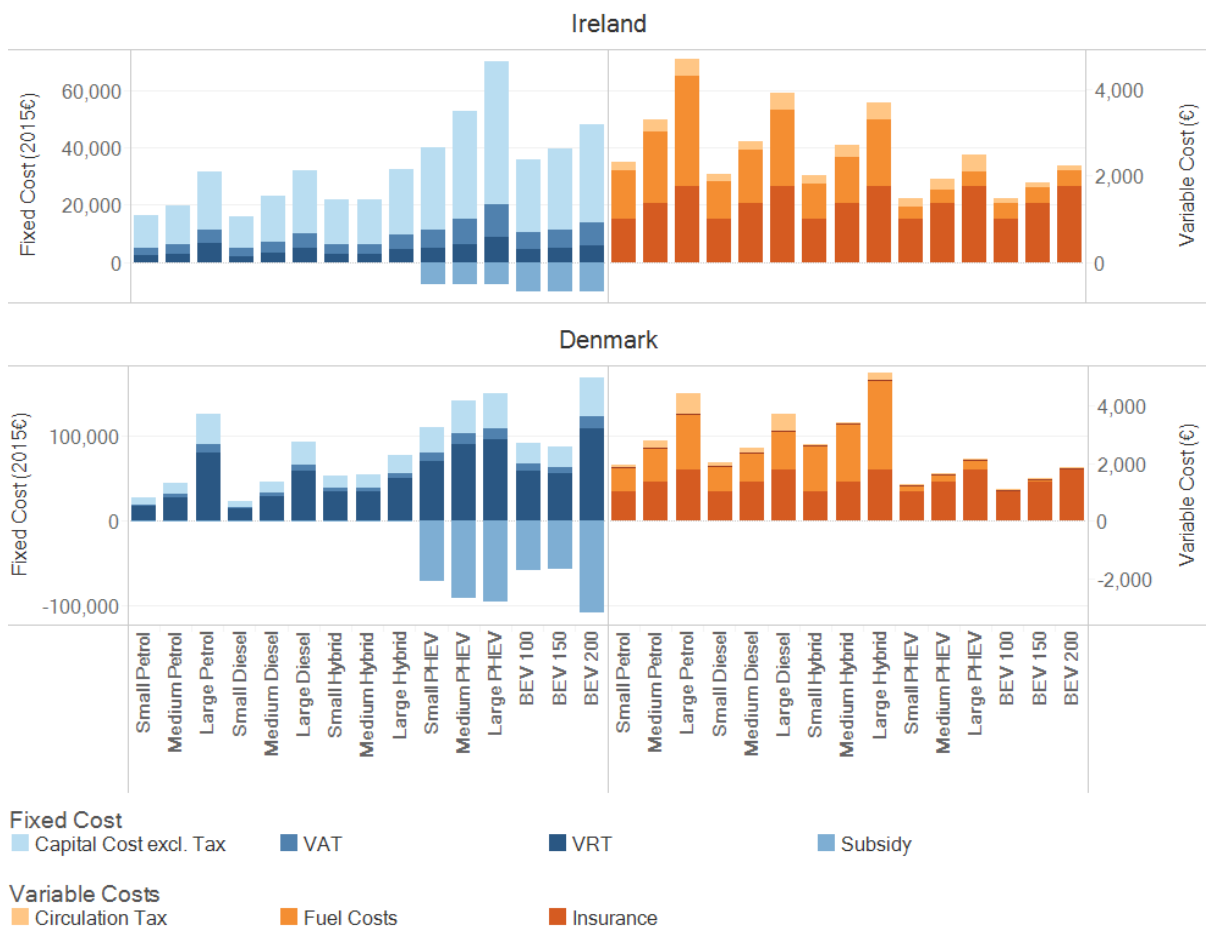


Figure 6.4: Tangible costs in 2015 of all the 15 technologies included in the scope of analysis

6.3.1.1.1 Projections of Variables

Projections of vehicle capital costs are taken from Argonne National Lab’s vehicle system simulation tool, Autonomie (Moawad et al., 2016), which has been used to compare a large number of powertrain configurations and component technologies. According to this model, the price of conventional ICEs is expected to increase due to measures required to improve vehicle fuel efficiency through light weighting, which is accompanied by an increase in the cost of materials such as aluminium or carbon fiber. An expected decrease in the cost of battery production and deployment results in a fall in the price of AFVs. A summary of these cost projections indexed against 2015 is shown in Figure 6.5, and further insights into Autonomie’s modelling framework can be found in Moawad et al. (2016).

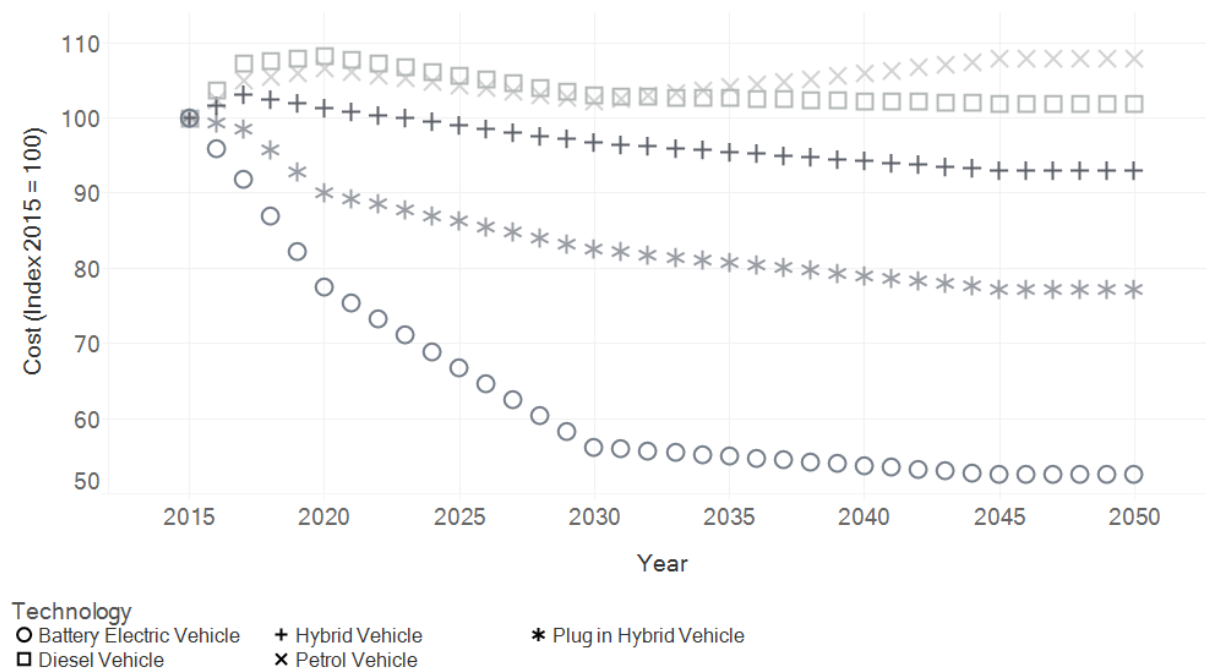


Figure 6.5: Assumed projections of the tangible costs of the vehicle categories in 2015 – 2050

In the Business as Usual scenario, the tax system currently in place is used to generate VRT and VAT for both countries, although scenarios are later formed through the derogation of these taxes. Annual fuel costs are determined as a product function of annual mileage, technology efficiency, and pump fuel prices, with variances in the annual cost of fuel for each consumer segment expected as both technology efficiency and fuel prices change. Fuel price changes for both countries were based on projections of the increase in fossil fuel import prices from Capros et al. (2013), while the improvements in vehicle energy efficiency were aligned with current European mandated

manufacturer standards (European Parliament, 2009a), and assuming maximum efficiency improvement by 2050 aligned with (IEA, 2008).

6.3.1.2 Intangible Costs

The role of intangible costs in these consumer choice models is to represent the non-monetary costs associated with vehicle purchasing as to draw a comparison between these intangible costs and the actual costs faced by consumers (tangible costs). Intangible costs have been introduced into consumer choice models as a means of providing more accurate competition between technologies in the past, e.g., McCollum et al. (2016), Bunch et al. (2015), and Kamiya (2015). This subsection identifies the means through which this study monetises the main intangible costs.

6.3.1.2.1 Model Availability/Risk Related Disutility

Empirical data were used to determine the intangible costs associated with model availability and risk related disutility across all technology classes and consumer segments based off the number of models of vehicles available for sale. Intangible costs are assumed to vary for consumers of varying driving profiles and adoption propensity. These intangible costs are applicable for all vehicles: a low representation of models available for a class of ICEs will pertain to a high intangible cost, as it would for AFVs. The primary difference between ICEs and AFVs in this respect relates to the current standing of the market, which is currently dominated by diesel and petrol ICEs in both Ireland and Denmark, indicating that these vehicles are at the latter stage of the diffusion of innovation curve (low relative risk related disutility), while AFVs are at an early stage (high relative risk related disutility). This section first discusses the methodology adopted in line with this logic to introduce a model availability disutility cost for both ICEs and AFVs.

6.3.1.2.1.1 ICE Model Availability Disutility

The competition between ICEs in a market independent of AFVs was initially analysed to determine the disutility cost associated with model availability for the late majority consumer segment – this study assumes that ICE vehicles are at the latter stage of Rogers’ diffusion curve, and are thus assumed to represent the late majority consumer segment. The share of AFVs sold in both Ireland and Denmark over the period analysed (2000 – 2015 for Ireland, 1985 – 2015 for Denmark) was 0.08% and 0.19% respectively, and thus assumed to have had a negligible impact on consumer choice of ICEs. As first discussed in Section 6.3, different consumer driving profiles relate to different sizes of vehicles in both countries. Therefore, the intangible cost related to model availability for

modest drivers, average drivers, and frequent drivers is determined by the available number of small sized cars, medium sized cars, and large sized cars respectively.

A non-linear intangible cost function depicting model availability was introduced and calibrated using the historic market share as a bench mark. The intangible cost relating to model availability varies by the number of models for each technology available, whereby a low number of a certain technology yields a high intangible cost, and vice versa (see Equation 6.4). Calibration of this function involved minimising the residual square error between the predicted and actual sales across each driving profile by varying the constants α and β for each driving profile (DP) within the Late Majority (LM) consumer segment. The values for these constants, along with the R^2 values when comparing the historic market share to that calculated by the consumer choice model after incorporating these generalised cost parameters is given in Table 6.3.

$$\text{Model Availability Intangible Cost}_{LM,DP} = \frac{\alpha_{DP}}{\beta_{DP} + \text{No. Models Available}_{DP}} \quad (6.4)$$

Table 6.3: Generalised cost curve parameters and corresponding R^2 for the frequent drivers consumer segment

		Modest Driver	Average Driver	Frequent Driver
Ireland	α	1.86E+05	2.16E+05	1.60E+06
	β	27.27	0.00	0.00
	R^2	0.998	0.899	0.832
Denmark	α	1.39+E06	1.51+E06	1.13+07
	β	192.87	119.75	439.67
	R^2	0.986	0.986	0.788

The number of models available for sale in Ireland between 2004 and 2015 of each technology is taken from the Society of the Irish Motor Industry (SIMI, 2017), as with the data for capital costs, while for Denmark a comprehensive list of models available from 1986 to 2008 is gathered from (FDM, 2017a). No comprehensive list of models available for sale was found for Denmark beyond 2008, so the number of different technology types sold (available from (EEA, 2017)) is used as an indicator for the rate of change in the model availability to 2015. The consumer choice model results with and without these cost curves are shown in Figure 6.6. It was deemed necessary to include these intangible costs as they enabled a stronger calibration of the model, shown in Figure 6.6, and provided a high R^2 value across each driving profile.

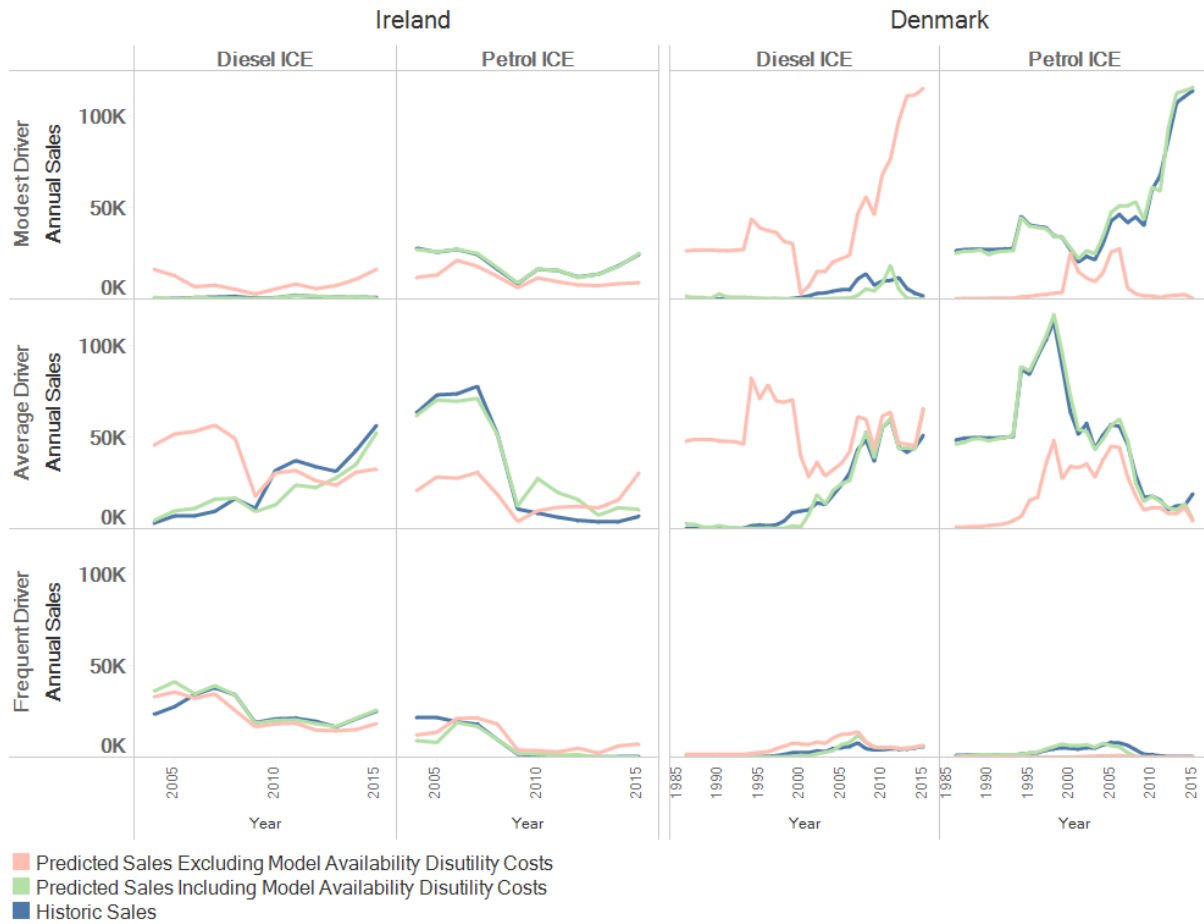


Figure 6.6: Consumer choice model results for ICE vehicles, with and without model availability disutility costs

6.3.1.2.1.2 AFV Model Availability and Risk Related Disutility

The nature of a risk related disutility, which has been adopted by this study, accounts for the varying level of perceived risk within each consumer segment - early adopters associate a lower risk with the purchase of an AFV relative to that associated by the late majority. In an attempt to monetise this risk using quantitative data, this study created a non-linear regression model to analyse the variance in intangible costs of AFVs with respect to the number of models available for sale across the EU-28 using the publicly available database from the Environmental Energy Agency (EEA) on vehicle sales from 2010 - 2015. Vehicle sales figures from these databases were extracted and used as an input for a European consumer choice model (using Equation 6.2), with the same structure as that of the Irish and Danish consumer choice models, to determine the intangible costs for consumers of AFVs within each of the 28 EU member states. Technologies were segmented to align with those used in the Irish and Danish consumer choice model, and tangible costs were calculated using the vehicle cost excluding taxes from the Irish and Danish databases, with the varying level of tax rates for each member state calculated according to (ACEA, 2015). The generalised intangible costs for AFVs were

then generated to align with market shares in each country in each year from 2010 to 2015. While the purpose of these databases was to show compliance with European emission standards, this study found a large number of discrepancies with the reporting of fuel types within the database. For example, in 2015 12,000 Citroen ICEs were wrongly reported as either ‘petrol and electric’ or ‘diesel and electric’ and subsequently published as PHEVs by the EEA. Furthermore, a large number of hybrids have been reported by the EEA as PHEVs. In 2015, the EEA reported approximately 126,000 PHEVs sold in Europe, although after manually correcting misreported fuel types within these EEA databases, the actual sale of PHEVs in 2015 was found to be closer to 82,000 vehicles. In the 2016 release of this database, no further discrepancies were found.

Finally, a non-linear regression analysis was carried out using these intangible costs as dependent variables and using the number of AFVs available for sale within each country, extracted from (EEA, 2017) as explanatory variables. Equation 6.5 was used to calculate the intangible cost pertaining to model availability for the early adopter (EM) consumer segment for different vehicles (v_e). The parameters of this equation were generated from the regression discussed above, as it assumes that all consumers of AFVs so far fall within the early adopter segment. To generate the parameters for the early majority segment, interpolation was carried out between the early adopter and late majority generalised cost curves. These factors are presented in Table 6.4.

$$\text{Model Availability Intangible Cost}_{EA,v} = \frac{1}{\alpha_{v_e} + \beta_{v_e} * \text{No. Models Available}_v} \quad (6.5)$$

Table 6.4: Generalised cost curve parameters for the early adopter and early majority consumer segments

Technology	Constant	Early Adopter	Early Majority (Interpolated)
BEV_100	α	7.70E-04***	3.85E-04
	β	5.49E-05	2.98E-05
BEV_150	α	4.27E-04***	2.14E-04
	β	3.19E-05***	1.83E-05
BEV_200	α	8.52E-05***	4.26E-05
	β	8.88E-06***	6.75E-06
PHEV Small	α	1.10E-04	5.50E-05
	β	3.38E-05***	1.98E-05
PHEV Medium	α	6.11E-05	3.05E-05
	β	1.96E-05***	1.21E-05
PHEV Large	α	1.22E-05	6.09E-06
	β	5.46E-06***	4.48E-06

***Statistical significance at the $p < 0.001$ level

6.3.1.2.2 Range Anxiety/Refuelling Infrastructure

Range anxiety is defined in this study as the perceived disutility faced by a consumer in failing to meet a desired travel demand due to shortages in battery charge availability. As a form of proxy, this study first attempts to consider the variation in intangible costs for all 28 EU member states compared against the variation in charging point availability, with the logic that range anxiety falls as the number of charging points rise. A regression was established to consider this variation using the intangible costs (determined in Section 6.2. above) and the number of public charging points available from ACEA (2017). This regression, however, was found to have a low level of significance, concluding that there was an insufficient level of information relating to private charging points (such as work and home charge points).

Therefore, this study employs a similar approach as used by McCollum et al. (2016), whereby the daily travel profiles of each consumer segment are calculated using the gamma distribution curves generated by the MA³T model, and the failure to meet the daily travel demand on one day ensues a penalty. The penalty used to encompass both range anxiety and refuelling infrastructure is chosen by calibrating the model results to national sales in 2015 and decreases linearly to the cost of renting a vehicle (€117.89 for Ireland and €186.04 for Denmark).⁵ The probability of BEV drivers meeting their daily travel demand is based on the number of charge points available (either a type 2 home charger, a type 2 work charger, or both) and the time spent charging (8 hours at home, 7 at work). All BEV drivers are assumed to have access to at least one private charging point, and introducing a second charging point reduced range anxiety.

6.3.2 Car Stock Model

The market shares are an output from the consumer choice model into the techno-economic private car sectoral simulation model to calculate the final stock, energy consumption, and emissions for both Ireland and Denmark. These stock models have the same structure of the CarSTOCK model described in Chapter 4, and draw upon detailed national data statistics relating to the composition of the market, sales, average mileage, efficiency, and life-time of vehicles with a disaggregation of vintage, fuel type and engine size to produce a long-term evolution of the private car stock, energy use and related CO₂ emissions to 2050 based off the ASIF methodology developed by Schipper et al. (2000) which can be summarised by Equation 6.6. In brief, total private transport related CO₂ is calculated as a sum of the product of vehicle activity (A), private car stock (S), energy intensity (I),

⁵ Prices for Denmark and Ireland were based off 54 and 85 quotes respectively from 5 different car rental companies

and emission factors (F) for fuel type (f) and vintage (v). Aggregate emissions for the private transport sector is obtained using this methodology for each of the 15 technologies analysed

$$\text{Transport Related } CO_2 = \sum_{f,v_i} A_{f,v_i} * S_{f,v_i} * I_{f,v_i} * F_f \quad (6.6)$$

Activity is recorded in an annual vehicle inspection for both countries, whereby the annual mileage of each vehicle in the country is recorded. This data was accessed through the Sustainable Energy Authority of Ireland (SEAI) who processed this raw data into technology specific data, and from accurate odometer readings from the Ministry of Transport (MOT) tests for Denmark.

Stock data in Ireland is obtained from the Vehicle Registration Unit, who provides a detailed list of vehicles, accounting for fuel type, engine size (ES) and vehicle vintage (v_i). This data for Denmark is obtained combining the inspection data of the Danish Road Directorate with the Administrative Car Register. As this chapter has previously shown that diverse technologies have different driving profiles (see Section 6.3 and Table 6.1), it can be assumed that there is a variation in the level of deterioration for each technology. For this reason, a survival profile is built to account for an accurate lifetime of each vehicle type using this information in tandem with Equation 6.7. The resulting probability of survival is presented in Figure 6.7.

$$\text{Survival Rate}_v^{ES} = \text{Average} \left(\frac{(Stock_v^{ES} - Stock_{v-1}^{ES})}{Stock_v^{ES}} \right) * (1 + \text{Survival Rate}_{v-1}^{ES}) \quad (6.7)$$

The oldest data available for Ireland was from the year 2000, resulting in survival profiles up to the age of 16 years being built. Data beyond this was extrapolated using an exponential decay in line with historic data. Data for Denmark was available since 1985, thus allowing for a more complete set of survival profiles to be formed.

Specific energy consumption of the historic fleet in Ireland disaggregated by engine band are obtained from the SEAI, who links national sales data of each vehicle to the manufacturer's specified energy consumption per km. Efficiency data for Denmark has been obtained combining the inspection data of the Danish Road Directorate with the Administrative Car Register. A comparison of the specific energy consumption of each vehicle type is shown in Table 6.5.

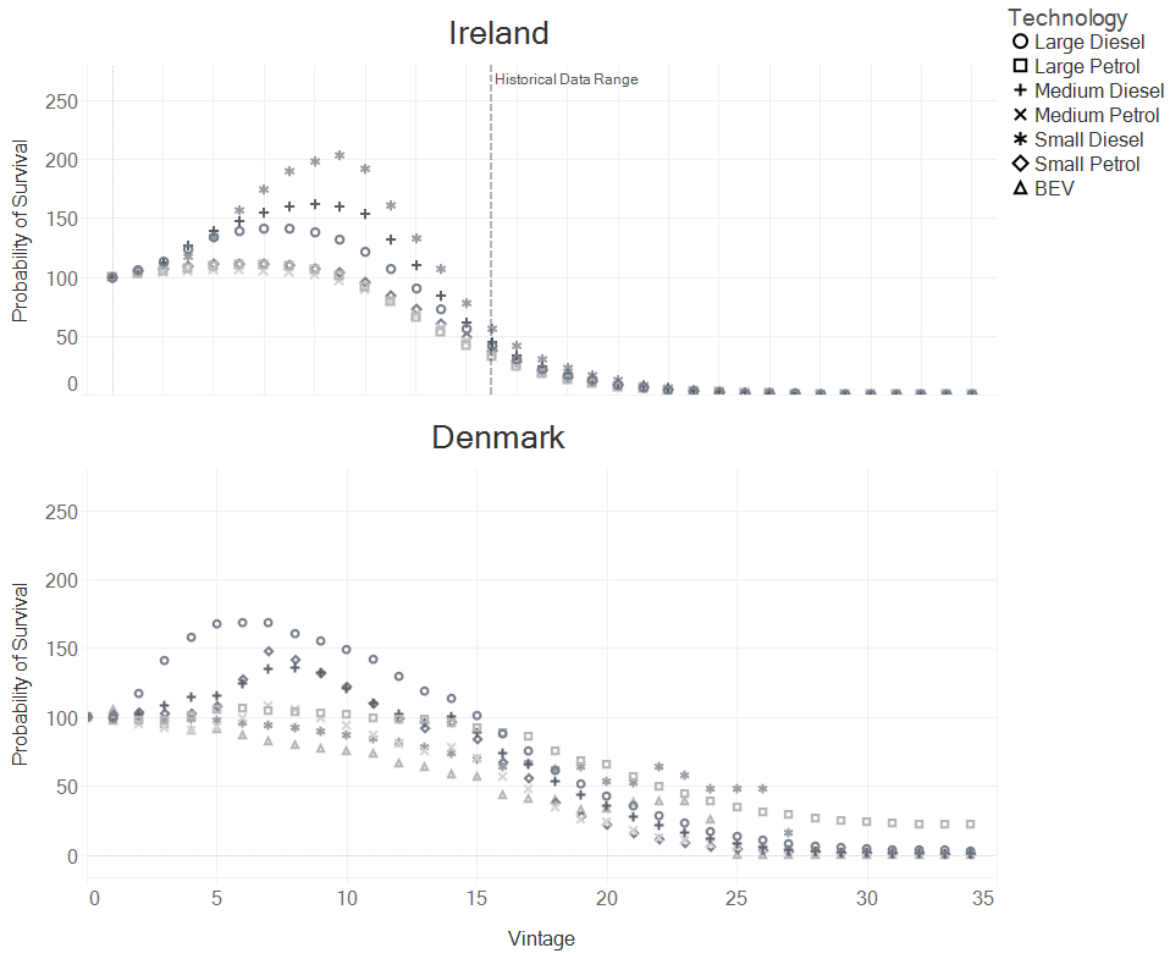


Figure 6.7: Irish and Danish technology survival profiles

Table 6.5: Specific energy consumption by class of car technology for Ireland and Denmark in 2015

Specific Energy Consumption (MJ/km)	Ireland	Denmark
Small Petrol	1.83	1.45
Medium Petrol	2.22	1.77
Large Petrol	2.70	2.73
Small Diesel	1.60	1.15
Medium Diesel	1.62	1.25
Large Diesel	2.19	1.82
Small Hybrid	1.38	1.38
Medium Hybrid	1.37	1.37
Large Hybrid	1.89	1.89
Small Plug in Hybrid	0.68	0.29
Medium Plug in Hybrid	0.68	0.69
Large Plug in Hybrid	0.77	1.00
Battery Electric Vehicle	0.64	0.62

The fuel emission factors for petrol and diesel were taken from Dineen et al. (2014). Relating to electricity emissions, both Ireland and Denmark have made recent strides towards a low carbon power sector, aiming for 40% and 50% renewable electricity by 2020 respectively (DCCAE, 2010), (Danish Energy Agency, 2015). Projections of electricity specific CO₂ emissions were taken from the EU PRIMES reference scenario, which assumes an emissions intensity in 2050 of 0.03 tCO₂/MWh in Denmark (down from 0.17 tCO₂/MWh in 2015) and 0.13 tCO₂/MWh in Ireland (down from 0.41 tCO₂/MWh in 2015) (European Parliament, 2016).

6.4 Results & Discussion

The consumer choice model produced satisfactory results of vehicle market shares for both the base year (2015) and first year of available data in both Ireland and Denmark (2004 and 1986 respectively). The resulting market share for both Ireland and Denmark in 2015, with and without intangible costs, are shown in Figure 6.8. The results highlight the importance of accounting for the non-monetary parameters in order to have a reliable model.

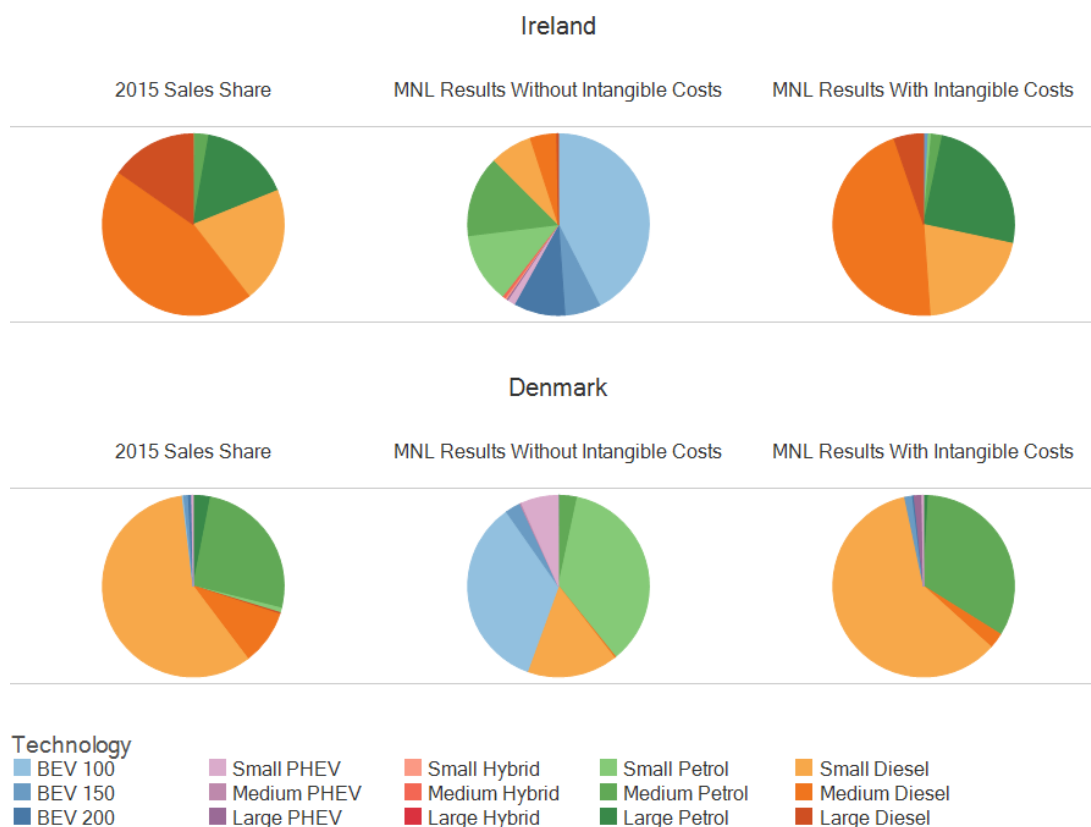


Figure 6.8: Historic and model market shares for Ireland and Denmark for 2015

In keeping with the original aim of this study - which sets out to determine the effect of revoking tax relief for BEVs and PHEVs, and to determine the cost and effectiveness of implementing further governmental level policy measures incentivising BEV and PHEV purchasing - the scenarios are set in a similar fashion. Firstly, a Business as Usual scenario (BaU) identifies the change in stock, emissions, and energy consumption from the base year to 2050 following a retraction of BEV and PHEV subsidies in line with currently national government policies in Ireland and Denmark. This scenario is developed upon whereby the impact of reducing the model availability of BEVs and PHEVs through increasing the number of models available for sale is explored. Secondly, multiple scenarios identifying the impact of government intervention, in tandem with external factors (i.e., beyond the control of national governance) are explored. These policy-induced interventions range from the reintroduction of a VRT subsidy for BEVs and PHEVs, introduction of a derogation of VAT for BEV and PHEVs, offering free electricity for vehicle charging, a derogation of AMT for BEVs and PHEVs, and a regulation of the sales of ICEs. The external factors explored detail the varying level of BEV and PHEV vis-à-vis varying the number of models available – as neither Ireland nor Denmark produce automobiles, they must rely on foreign manufacturers to produce more BEV or PHEV models to reduce the model availability intangible cost. Finally, the cost and corresponding market uptake associated with the introduction of these monetary controlled incentives are presented.

The remainder of this section summarises the market shares calculated by the consumer choice model and the resulting final stock and emissions figures under these scenarios. These results represent the combination of the 18 consumer segments, but are the representation of the entire national market. Figure 6.9 presents the various costs within the consumer choice model for one specific consumer segment - the urban, modest driver, early adopter segment for Ireland under a BaU. In this sample scenario, the capital costs for ICEs increase and the capital cost for BEVs and PHEVs decrease, while the model availability intangible costs for BEVs and PHEVs reduce due to a linear increase in the number of models available for sale. These changes in costs increase vehicles competitiveness within the model and increase the market share for AFVs. Each segment is calculated individually and later combined to give a comprehensive representation of the national car stock market.

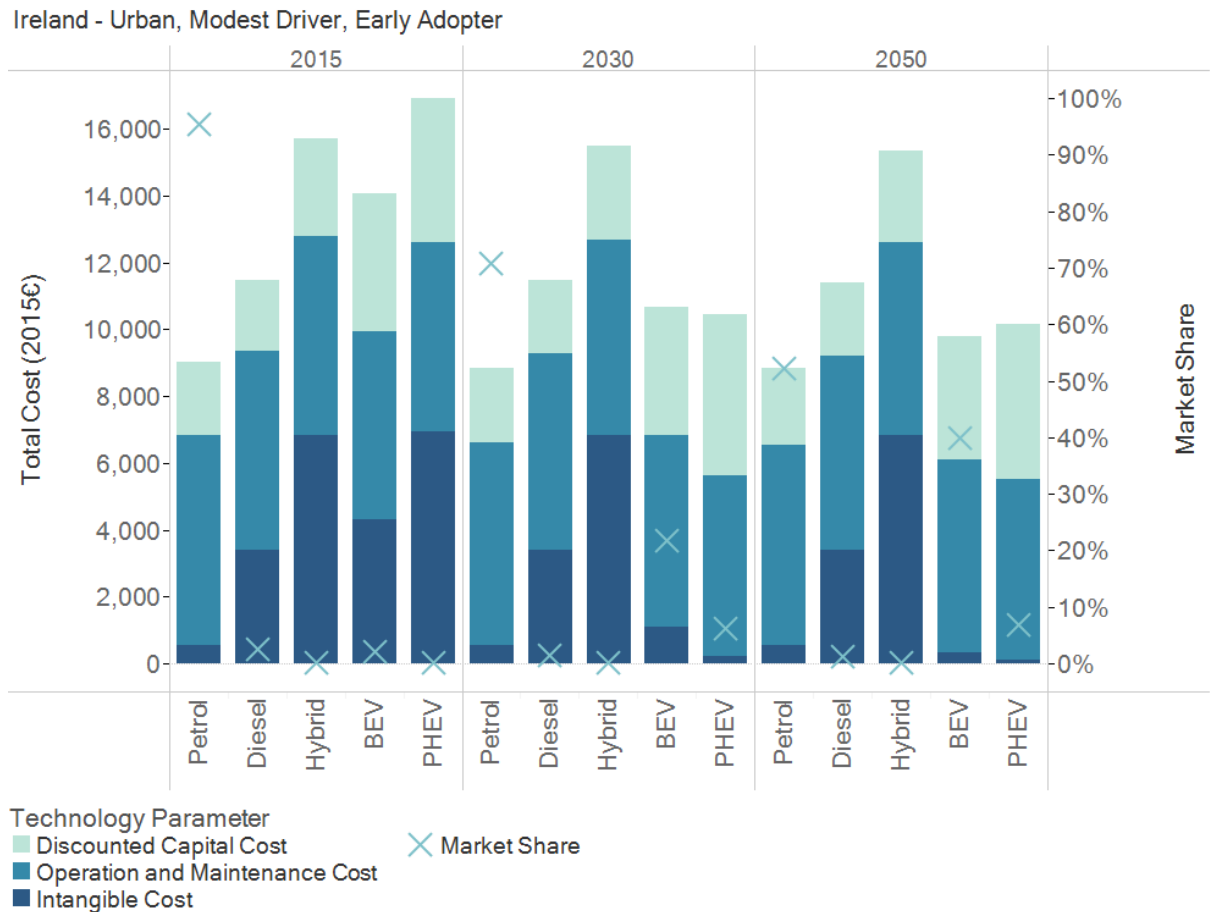


Figure 6.9: Market share and associated costs for BaU with an increase in BEV/PHEV models available

6.4.1 VRT Subsidy Removal – BaU

6.4.1.1 Ireland

Under a BaU with no variation in the number of models available for sale, the market share of BEVs in Ireland rises from 0.39% in the base year to 1.2% in 2021, and then falls to 0.3% once the VRT subsidy is removed in 2022. This market share rises steadily to 4.5% by 2050, driven by the assumed reductions in the cost of BEVs and cost increases in ICEs (Moawad et al., 2016). The market share of PHEVs largely goes unchanged. The market share of AFVs in the base year stands at 0.002%, and following the removal of the VRT subsidy in 2019, this is reduced to 0.001%. Despite reductions in the cost of this technology, there is no change in the market share by 2050 due to the low level of PHEV models available. Total AFV stock reaches 91,000 vehicles by 2050, with 3.46 million ICEs.

Emission reductions are still evident despite the low uptake of AFVs driven by ICE efficiency improvements. These efficiency improvements are in line with current European standards of manufacturer's achieving a maximum of 95gCO₂/km per vehicle produced by 2021 (European Parliament, 2009a) and a regulatory proposal of setting this standard to between 68 – 78gCO₂/km

for 2025 (Mock, 2013). Efficiency improvements beyond this are assumed at a year-on-year value of 0.75%, in line with the total long-range potential efficiency improvements of ICEs by 2050 according to (IEA, 2008). These efficiency improvements coupled with the marginal electrification of transport provide a 19% reduction in well-to-wheel CO₂ emissions by 2050 relative to 2015.

A linear increase in the model availability of BEVs and PHEVs from their current standing to match the number ICE models currently available reduces the intangible costs for these technologies significantly and by 2050 increases their combined market share to 49%. This corresponds to approximately 1.4 million BEVs and 75,000 PHEVs in the private vehicle stock by 2050, and a 44% reduction in well-to-wheel CO₂ emissions relative to 2015.

6.4.1.2 Denmark

The initial retraction of the VRT subsidy in 2016, whereby BEV/PHEV consumers must pay 20% of the tax payable, sees a sharp fall in total market share of these vehicles. ADF market shares falls from 3.2% in 2015 to 0.7% in 2020 when the subsidy is completely removed. The assumed improved efficiency within ICE vehicles increases competitiveness due to lower fuel costs, which in tandem with the assumed changes in the technology costs contributes to a marginal increase in market share of BEVs and PHEVs to a combined value of 1.7% in 2050. Total AFV stock reaches approximately 50,000 vehicles in 2050, while ICEs retain the lion's share at 3.64 million vehicles. Similar to the Irish results, this AFV penetration combined with the assumed efficiency improvements in ICEs generates an 18% reduction in WTW CO₂ emissions by 2050 relative to 2015, despite a 54% increase in total national vehicle stock over the same time period.

Increasing the number of AFV models available for sale to match that of ICEs in 2015 by 2050 results in a low increase in the market share of both BEVs and PHEVs, rising to 2.7% in 2050. This corresponds to a stock of 88,574 AFVs in 2050, and a reduction in WTW CO₂ emissions of 19% by 2050 relative to 2015. The uptake of AFVs is significantly lower than that of Ireland due to the significant rise in costs of EVs and PHEVs following the retraction of the VRT subsidy.

6.4.2 Governmental Policy Levers

The purpose of policies which act in favour of AFVs are, in general, to incentivise the sale of a new technology to a point where they overcome the initial barriers associated with purchasing and begin to achieve a greater market share. If incentives are drawn back too soon, they can prove ineffective. If incentives remain for too long, they may prove overly expensive. For this reason, 3 targets are set

– achieving a 10%, 50% and 80% market share penetration. In each of these scenarios, once the market share is achieved, the subsidy is ceased. Values marked with an asterisk in Table 6.6 signify success in meeting this target, while other figures represent a failed target. The scenarios for this analysis are divided into both monetary policy levers – offering a derogation of VRT, VAT, AMT, and offering free fuel for AFVs – and non-monetary policy levers – banning the sale of ICEs in 2030 with a 5 year phase in period. This latter policy lever is chosen to be in line with the Irish stated national ambition that by 2030 all new cars and vans sold in Ireland will be zero emission capable (DTTAS, 2017), which roughly follows recent ambitions by France and the United Kingdom to ban the sale of petrol and diesel cars by 2040 (Department for Environment, 2017, Ministère de la Transition, 2017). An externality to the model is the number of AFV models available for sale, as both Ireland and Denmark are vehicle ‘takers’ rather than vehicle ‘makers’. This attribute is classified into a ‘low’ scenario, where there is no change to the number of AFV models available, a ‘medium’ scenario, where by 2050 there are half of the number of AFV models available as there are currently ICEs, and a ‘high’ scenario, where the number of AFVs and ICE models available in 2050 is equal.

The monetary results in Table 6.6 represent the combined annual tax revenue foregone and cost of incentive (in the case of ‘No Refuelling Costs’) of that scenario relative to the BaU. For this reason, the ‘No Incentive’ policy could still result in a loss to the exchequer as the taxes paid by AFV consumers are, in general, lower than that of ICEs. The percentages in Table 6.6 represent the WTW CO₂ emissions reduction relative to the base year.

Placing an early ban on the sale of ICEs was found to have the cost optimal impact on the uptake of AFVs, with the penetration target met in 88 of the 90 scenarios run. In the case when no incentives are offered, there is generally a loss in revenue relative to the BaU due to the relatively cheaper nature of AFVs. In the scenario without any incentive offered, a high AFV model availability and a ban on the sale of ICEs, the average annual loss in tax to the exchequer is €169.7m/year in Ireland (resulting in an 89.3% AFV penetration) and €408.2m/year (resulting in an 86% AFV penetration) in Denmark, where the relative higher loss in Denmark is due to the higher rates of tax. In some rare cases, there is a net gain in tax revenue (signified by a negative value in Figure 6.10) due to the greater purchasing of AFVs close to the base year, when investment costs are relatively higher compared against ICEs which, in turn, yields a higher tax. In the case where no limit is placed on the sale of ICEs, the AFV target was achieved in just 25 scenario runs out of 90, with an 80% AFV penetration only met in 1 scenario (high availability of AFVs + VAT derogation in Ireland).

Table 6.6: Tax foregone/cost of incentive (in million 2015€ per annum) and % WTW CO₂ emission reductions in 2050 relative to 2015

Country	Scenario		No Ban on ICE Sales			Ban on ICE Sales by 2030		
			Low AFV	Med AFV	High AFV	Low AFV	Med AFV	High AFV
			Model	Model	Model	Model	Model	Model
			Availability	Availability	Availability	Availability	Availability	Availability
Ireland	10% AFV Target	No Incentive	€0m/19.9%	€101m/54.4%*	€114.1m/59.1%*	€162.3m/68%*	€179.5m/68.8%*	€169.7m/69.5%*
		VRT Derogation	€24.2m/20.5%	€130.9m/54.5%*	€147.1m/59.1%*	€187.7m/68%*	€207.1m/69%*	€200.9m/69.6%*
		VAT Derogation	€43.6m/21%	€141.3m/54.6%*	€155.3m/59.3%*	€202.6m/68.1%*	€216.9m/69.1%*	€208.6m/69.8%*
		AMT Derogation	€1.5m/20%	€101.8m/54.4%*	€114.5m/59.1%*	€163.1m/68%*	€179.6m/68.8%*	€169.8m/69.5%*
		No Refuelling Costs	€6.4m/20.6%	€102m/54.6%*	€112.9m/59.2%*	€164.5m/68%*	€178.5m/69%*	€167.7m/69.7%*
	50% AFVs Target	No Incentive	€0m/19.9%	€101m/54.4%*	€114.1m/59.1%*	€162.3m/68%*	€179.5m/68.8%*	€169.7m/69.5%*
		VRT Derogation	€24.2m/20.5%	€292.5m/56.5%*	€302.6m/60.6%*	€316.1m/68%*	€339.1m/69.3%*	€336.4m/70%*
		VAT Derogation	€43.6m/21%	€391.5m/57.2%*	€374.2m/61%*	€399m/68.1%*	€420.9m/69.8%*	€400.8m/70.6%*
		AMT Derogation	€1.5m/20%	€110.4m/54.7%*	€121.8m/59.3%*	€168.9m/68%*	€185.2m/68.9%*	€175.1m/69.5%*
		No Refuelling Costs	€6.4m/20.6%	€124.8m/56.6%*	€130.9m/60.6%*	€181.6m/68.1%*	€194.6m/69.3%*	€181.6m/70%*
	80% AFVs Target	No Incentive	€0m/19.9%	€101m/54.4%	€114.1m/59.1%	€162.3m/68%	€179.5m/68.8%*	€169.7m/69.5%*
		VRT Derogation	€24.2m/20.5%	€484.4m/60%	€561.5m/64.1%	€535.5m/68.1%*	€523.7m/69.2%*	€520.8m/70%*
		VAT Derogation	€43.6m/21%	€748.7m/62.6%	€825.8m/65.9%*	€733.8m/68.1%*	€701.7m/69.7%*	€705.8m/70.6%*
		AMT Derogation	€1.5m/20%	€114.9m/54.7%	€130.4m/59.4%	€179.2m/68%	€193.6m/68.9%*	€183.6m/69.6%*
		No Refuelling Costs	€6.4m/20.6%	€154.4m/59.6%	€173.4m/63.7%	€211.5m/68.1%*	€219.9m/69.4%*	€206.7m/70.1%*
Denmark	10% AFV Target	No Incentive	€0m/17.6%	€16.3m/18.7%	€19m/18.9%	€105.8m/76.4%*	€325.9m/76.6%*	€433.8m/76.7%*
		VRT Derogation	€165.9m/19.3%	€433.6m/24.7%*	€452.9m/24.9%*	€715m/77.8%*	€718.3m/78.4%*	€731.9m/78.1%*
		VAT Derogation	€42.5m/18.3%	€50.2m/19.1%	€66.8m/19.7%	€402.4m/76.6%*	€494.9m/77%*	€582.6m/77.1%*
		AMT Derogation	€0.9m/17.6%	€16.6m/18.7%	€19.4m/19%	€108.6m/76.4%*	€326.7m/76.6%*	€434.5m/76.7%*
		No Refuelling Costs	€3.7m/17.7%	€13.6m/18.7%	€16.6m/19%	€296.3m/76.4%*	€465.9m/76.7%*	€555.7m/76.7%*
	50% AFVs Target	No Incentive	€0m/17.6%	€16.3m/18.7%	€19m/18.9%	€105.8m/76.4%*	€325.9m/76.6%*	€433.8m/76.7%*
		VRT Derogation	€165.9m/19.3%	€1,761.7m/51.6%*	€1,865.5m/53%*	€1,382m/77.8%*	€1,462.7m/81%*	€1,475.3m/81.3%*
		VAT Derogation	€42.5m/18.3%	€50.2m/19.1%	€66.8m/19.7%	€589.8m/76.6%*	€705.4m/77.1%*	€766.2m/77.2%*
		AMT Derogation	€0.9m/17.6%	€16.6m/18.7%	€19.4m/19%	€109.8m/76.4%*	€328.1m/76.7%*	€435.9m/76.7%*
		No Refuelling Costs	€3.7m/17.7%	€13.6m/18.7%	€16.6m/19%	€274.7m/76.4%*	€444.2m/76.7%*	€533.9m/76.7%*
	80% AFVs Target	No Incentive	€0m/17.6%	€16.3m/18.7%	€19m/18.9%	€105.8m/76.4%*	€325.9m/76.6%*	€433.8m/76.7%*
		VRT Derogation	€165.9m/19.3%	€2,009.1m/59.5%	€2,323.8m/65.4%	€2,219m/77.7%*	€2,378.5m/81.3%*	€2,418.8m/81.7%*
		VAT Derogation	€42.5m/18.3%	€50.2m/19.1%	€66.8m/19.7%	€797.1m/76.6%*	€924.7m/77.1%*	€1009.2m/77.3%*
		AMT Derogation	€0.9m/17.6%	€16.6m/18.7%	€19.4m/19%	€111.3m/76.4%*	€330.9m/76.7%*	€438.7m/76.7%*
		No Refuelling Costs	€3.7m/17.7%	€13.6m/18.7%	€16.6m/19%	€222.1m/76.4%*	€383.1m/76.7%*	€475.9m/76.7%*

* Signifies that the AFV target was met in the given scenario

While all 90 scenario runs are presented in Table 6.6, Figure 6.10 presents the market share and associated cost to the exchequer for four scenarios defined as follows:

- i. S1 – Low AFV model availability, no ban on the sale of ICEs, no further incentives offered (BaU)
- ii. S2 – High AFV model availability, no ban on the sale of ICEs, no further incentives offered
- iii. S3 – Medium AFV model availability, ban on the sale of ICEs in 2030, no further incentives offered
- iv. S4 - Medium AFV model availability, no ban on the sale of ICEs, derogation of VAT, VRT, AMT, and no refuelling costs from 2015

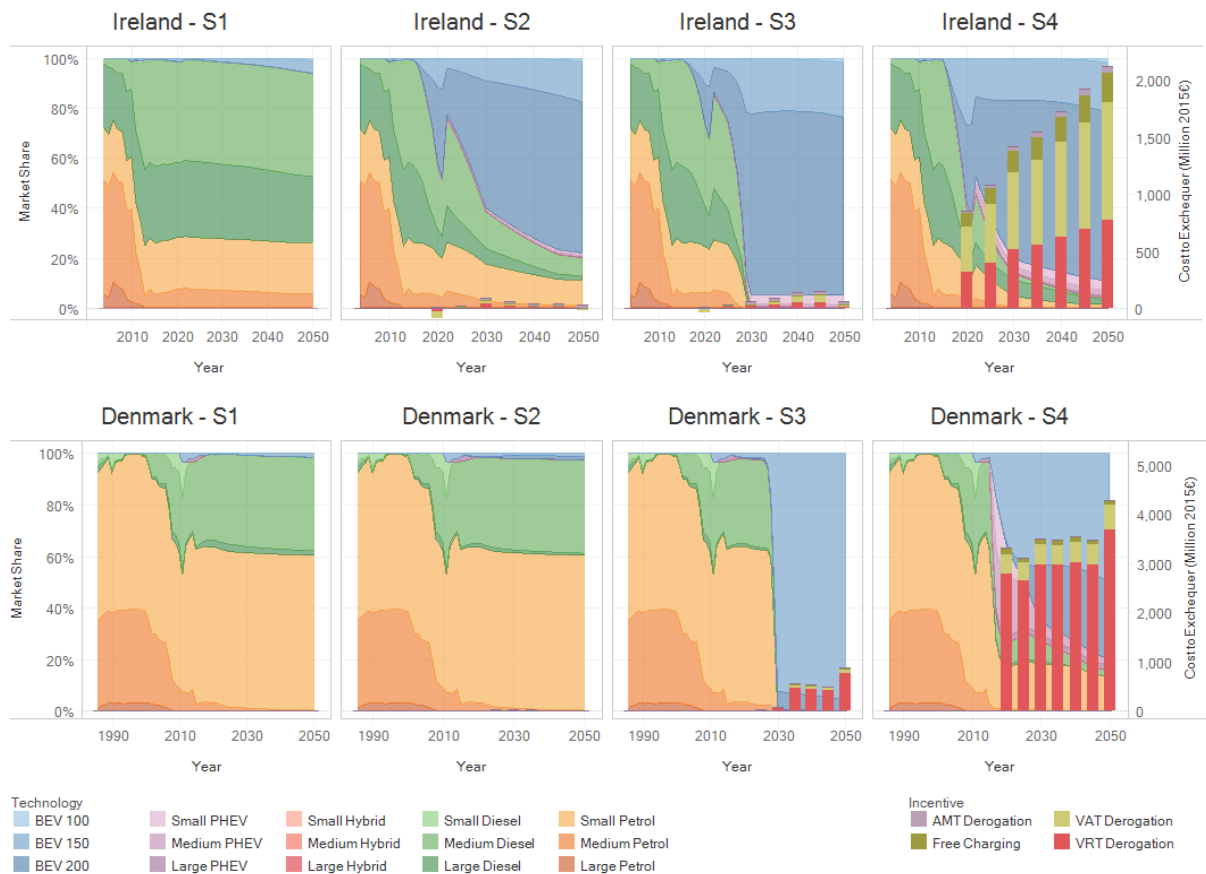


Figure 6.10: Market share and annual cost to the exchequer

S1 in both countries represents the initial question aimed at in this study – what will be the effect of the VRT subsidy retraction. The other question posed by this study, which focused on the cost and effect of further incentivisation of AFV purchasing, are answered in scenarios S2 through S4. The high costs associated with the Danish VRT system create great difficulty in a penetration of AFVs in S2, where the disutility from model availability is largely reduced due to an increase in the number

of AFVs available for sale. In the same scenario in Ireland, while the VRT subsidy retraction for BEVs causes a drop off in market sales in 2022, BEVs start to emerge strongly in the market through to 2050. In S3, whereby a ban is placed on the sale of ICEs, and there are half as many AFVs available for sale in 2050 as ICEs, a much faster emergence of AFVs is seen, although the Danish government start to face large drops in revenue from VRT and VAT tax foregone, amounting to €1.1 billion in 2050 alone. Finally, in the costliest scenario, S4, where there is no ban on the sale of ICEs, and there is a derogation of VRT, VAT, AMT, and no refuelling costs, there is a fast uptake of AFVs in both Ireland and Denmark, yet this comes at a significant cost to the exchequer, €4.3 billion in Denmark and €2.1 billion in Ireland in 2050.

6.5 Conclusions and Policy Recommendations

It is both challenging and expensive to electrify the private transport sector in Ireland and Denmark. To arrive at this conclusion, this study creates a consumer choice model which accounts for the costs and disutilities of 15 technologies available to Irish and Danish consumers linked with a simulation model corresponding to each country's private vehicle sector. The purpose of the study is to identify the effect of the currently planned retraction of the vehicle registration tax (VRT) subsidy in Ireland and Denmark, and to assess at what cost and level of effectiveness further incentives may aid in promoting the sale of low carbon vehicles.

In line with these aims, the study finds that retracting the VRT subsidies in accordance with both Irish and Danish national policies will result in a low penetration of alternative fuelled vehicles (AFV) through to 2050. This is especially true in Denmark where there is currently a very generous VRT subsidy, despite the expected decrease in capital costs of battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) (a combined 4.5% market share in Ireland in 2050, up from 0.39% in 2015 and 1.7% in Denmark in 2050, up from 1.6% in 2015).

A high penetration of AFVs in both countries was achieved through placing a ban on the sale of internal combustion engine (ICE) vehicles by 2030, although this comes at a loss to the exchequer in the form of tax foregone as AFVs, on average, are expected to cost less than ICEs in the future and therefore bring in less tax. Placing this ban achieves over an 80% penetration of AFVs by 2050 and comes at an opportunity cost through tax foregone in the range of €162m-€170m/year for Ireland and €106m-€434m/year for Denmark, dependent on the availability of AFV models for sale. Without regulating the sales of ICEs, Ireland could still achieve a substantial market penetration through a derogation of VAT on AFVs, but this comes at a higher average opportunity cost of €826m/year. This

same market penetration was found to be impossible through single incentives in Denmark, although a combination of VRT and VAT derogation on AFVs provide an 86% stock share by 2050 at an average loss to the exchequer of €3.6b/year.

This challenge and high cost of electrifying private transport is largely due to the number of high disutility costs preventing a large market penetration, but particularly due to the disutility cost associated with the low number of models of BEVs and PHEVs currently available for sale relative to ICEs. This is impossible to be overcome through national policy interventions in Ireland or Denmark, as neither country produces automobiles, while their cumulative demand of vehicles is quite low relative to all of Europe, accounting for approximately 2.5% of all European vehicle sales (EEA, 2017). A European wide policy focusing on increasing the number of AFV models available, such as the Zero Emission Vehicle Program adopted by 9 states in the US (CARB, 2009), may be necessary to overcome this barrier whereby manufactures are mandated to sell AFVs.

Further work to this study would include a more thorough analysis of the vehicle market. This study assumed the number of ICEs available for sale did not change from the base year (with the exception of the ban placed on the sale of such vehicles) although in reality the market has a tendency to fluctuate based on a variety of factors. This study is also constrained by the number of behaviour attributes considered within this modelling framework. While this study modelled the intangible costs from model availability, risk related disutility, range anxiety, and refuelling/recharging infrastructure availability, there are a plethora of other preferences which consumers may have when purchasing a vehicle that are outside of the scope of this study.

Chapter 7

A Long-term Strategy to Decarbonise the Danish Road Transportation Sector

Abstract:

The 21st meeting of the Conference of Parties witnessed several Governments pledging commitments for their countries to provide deep cuts to energy-related CO₂ emissions as a means to maintain the rise of global temperature to well-below two degrees. This chapter utilizes a novel modelling framework to assess how alternative policies might contribute to a fossil-free transportation sector for one of these countries, Denmark, and the potential contribution they have to a well-below two degree world. The approach adopted consists of linking an optimization energy system model, TIMES-DKMS, with the private car simulation model, the Danish Car Stock Model developed in Chapter 6. The magnitude of CO₂ abatement is presented alongside the corresponding change in tax revenue generated through combinations of policies focusing on the derogation of motor taxes for low emission vehicles and banning the sale of the internal combustion engine. Finally, the cumulative emissions from the Danish energy system are compared to a range of national carbon budgets, calculated within this chapter to adhere to various levels of global temperature rise (1.5°C - 4°C) at different levels of confidence (33% - 66%). A ban on the sale of the internal combustion engine enforced in 2025 would enable the largest cut in cumulative GHG emissions of all the policies considered with a consequent increase in Exchequer revenue. However, none of the policies analysed were compliant with Denmark's carbon budgets capable of maintaining the increase of global temperature to below 2°C.¹

¹ Chapter based off a submitted book chapter to the upcoming ETSAP Book to be published by Springer: Tattini, J., Mulholland, E., Venturini, G., Ahanchian, M., Gargiulo, M., Balyk, O., Karlsson, K., "A long term strategy to decarbonise the Danish road transportation sector", Chapter in Springer Book "Towards a well below 2°C World: Moving to feasible zero-carbon roadmaps", Submitted in October 2017

7.1 Introduction

The 21st meeting of the Conference of Parties (COP21) hosted in November 2015 marked a momentous occasion, whereby a global agreement to combat climate change was ratified by 157 parties and adopted under the United Nations Framework Convention on Climate Change (UNFCCC). This agreement proposed to hold the increase in global temperature rise to well below 2°C above pre-industrial levels, and to pursue efforts to limit temperature increase to 1.5°C above pre-industrial levels (UNFCCC, 2016). To support this proposal, signatories have submitted Intended National Determined Contributions (INDCs) which provide roadmaps addressing the intended efforts to be made by countries to comply with this limitation of temperature rise, largely made through implied reductions in greenhouse gas (GHG) emissions which have been strongly linked to global temperature rise (IPCC, 2014a). However, achievement of the currently proposed INDCs would not comply with limiting global temperatures to 1.5°C, but rather imply a median warming of 2.6°C – 3.1°C by the end of the century (Rogelj et al., 2016).

Limiting global temperature rise to 1.5°C above pre-industrial levels relates to a total carbon budget, as of 2011, of between 400 GtCO₂eq and 850 GtCO₂eq for a respective possibility of achievement varying between >66% and >33% (IPCC, 2014a). While each signatory of the COP21 agreement will play a varied role in adhering to these carbon budgets, there has yet to be conformity for the equitable sharing of national carbon budgets. Two commonly proposed structures allocate carbon budgets based on the distribution of emissions (known as ‘grandfathering’, or ‘inertia’) and reflecting population distribution (known as ‘equity’) (Raupach et al., 2014). This chapter creates a range of provisional carbon budgets for Denmark using a combination of these two structures and focuses on the potential of policies aimed at the inland transport sector in complying with these budgets. Denmark is chosen as a case study following the ambitious target set by the Danish Government to decarbonise the entire energy system by 2050 (The Danish Government, 2011). Furthermore, the inland transport sector is given focus considering that it contributed to 28% of total energy consumption in 2015 in Europe (Eurostat, 2017b). So far, attempts to encourage renewables within the transport sector have been largely offset by an increase in transport activity and a lack of alternatives available. The retraction of the vehicle registration tax (VRT) subsidy for battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) saw a fall in the sale of these vehicles in 2016 (EEA, 2017), previously discussed in Chapter 6. Significant levels of policy intervention are required to reduce the transport sector’s reliance on fossil fuels. The study aims at determining the contribution of policies to decarbonise the inland passenger transport sector and to calculate national cumulative CO₂ emissions, which is then compared to a range of carbon budgets

necessary to contribute to limit global temperature rise. In particular, this chapter aims to answer the following research questions:

1. How much GHG emissions reduction can be achieved in Denmark through policies focusing on inland passenger transport?
2. Will the cumulative GHG emissions up to 2050 exceed the carbon budget available for Denmark, calculated based on the population and emissions sharing method from Raupach et al. (2014), to maintain the average global temperature rise to well below 2°C?

An innovative modelling framework is adopted which links a techno-economic optimisation energy systems model of Denmark - TIMES-DKMS - with a hybrid techno-economic and socio-economic simulation of the Danish private car sector - the Danish Car Stock Model (DCSM) - to provide realistic answers to the research questions underlying this study. The representation of the transportation sector within TIMES-DKMS features endogenous modal shift and, moreover, DCSM consists of a private car consumer choice model linked with a sectoral simulation model which is integrated in the model framework to represent the heterogeneous nature of the private car sector. A variety of policy packages aimed at reaching an ambitious decarbonisation of the inland transportation sector are implemented iteratively in both TIMES-DKMS and the supporting simulation models.

The remainder of this chapter is arranged as follows: Section 7.2 introduces the model framework and the calculation of the carbon budgets and the description of the scenarios analysed. Section 7.3 presents the results, focusing on modal shift within passenger transport, private light-duty vehicle purchasing, inland transport fuel consumption, inland transport greenhouse-gas (GHG) emissions and overall energy system emissions. Section 7.4 discusses the results while Section 7.5 provides some concluding remarks.

7.2 Methodology

This chapter uses an original modelling framework, which integrates TIMES-DKMS - the national energy system model of Denmark equipped with modal shift add-on (Tattini et al., 2017a) - with the Danish Car Stock Model (DCSM) - a consumer choice model of the private transport sector accompanied by a sectoral simulation model of the private car sector (see Chapter 6). This framework is used to model policies related to inland transport, calculate the consequent GHG emissions reduction, and determine the resulting long-term effect on exchequer revenue.

7.2.1 TIMES-DKMS

This study adopts the Denmark TIMES model with a modal shift add-on (TIMES-DKMS), which is constructed using a TIMES framework (The Integrated MARKAL EFOM System), a model generator developed by the Energy Technology Systems Analysis Program (ETSAP) – a technology collaboration programme of the International Energy Agency (IEA) (Loulou et al., 2005). TIMES is a partial equilibrium, linear optimization model which determines a least-cost solution for the energy system, subject to certain constraints. TIMES performs a simultaneous optimisation of operation and investments across the represented energy system over the modelling horizon (to 2050). It is based on a bottom-up techno-economic approach, as it has a database of technologies characterised by a high technical, economic and environmental detail. These characteristics make it a powerful tool for energy planners to identify the most cost-effective portfolio of resources and technologies to fulfil future energy-service demands under several constraints. A detailed description of TIMES is provided by Loulou et al. (2005).

TIMES-DKMS is a multi-regional TIMES model, covering the entire Danish energy system. It is geographically aggregated into two regions, with technological and economic projections to 2050. TIMES-DKMS is composed of five sectors: supply, power and heat, transport, industry and residential (Balyk et al., 2017). The transport sector in TIMES-DKMS includes the explicit representation of passenger and freight transport, both split in the aviation, maritime and inland transport sectors. Within the scope of this study, a focus is placed on inland passenger transport, which includes private car, bus, coach, rail (metro, train, S-train), 2-wheeler (motorcycle and moped) and non-motorized modes (bike and walk). Within the inland passenger transport sector, TIMES-DKMS determines modal shares endogenously. This feature provides additional flexibility to the model framework, which can fulfil environmental goals by increasing the market shares of some modes at the expense of others. The mode- and length-specific transport service demands are merged into length-only specific transport service demands, thus enabling competition between modes. Modal competition is based on both the levelised costs of the modes and on the parameters of speed and infrastructure requirements within the TIMES framework. Infrastructure accounts for the cost of adapting the existing transport networks to demand increases and possible significant modal shift. Modal speeds are complemented by a constraint on the total travel time budget (TTB), historically observed for the Danish transport sector (Transport DTU, 2016). Moreover, constraints on the maximal and minimal modal shares and on the rate of shift (derived from the Danish National Travel Survey) are included in TIMES-DKMS to guarantee the behavioural realism of the shift. A more

detailed description of TIMES-DKMS is provided in Tattini et al. (2017a), and Figure 7.1 provides a schematic description of the structure of TIMES-DKMS.

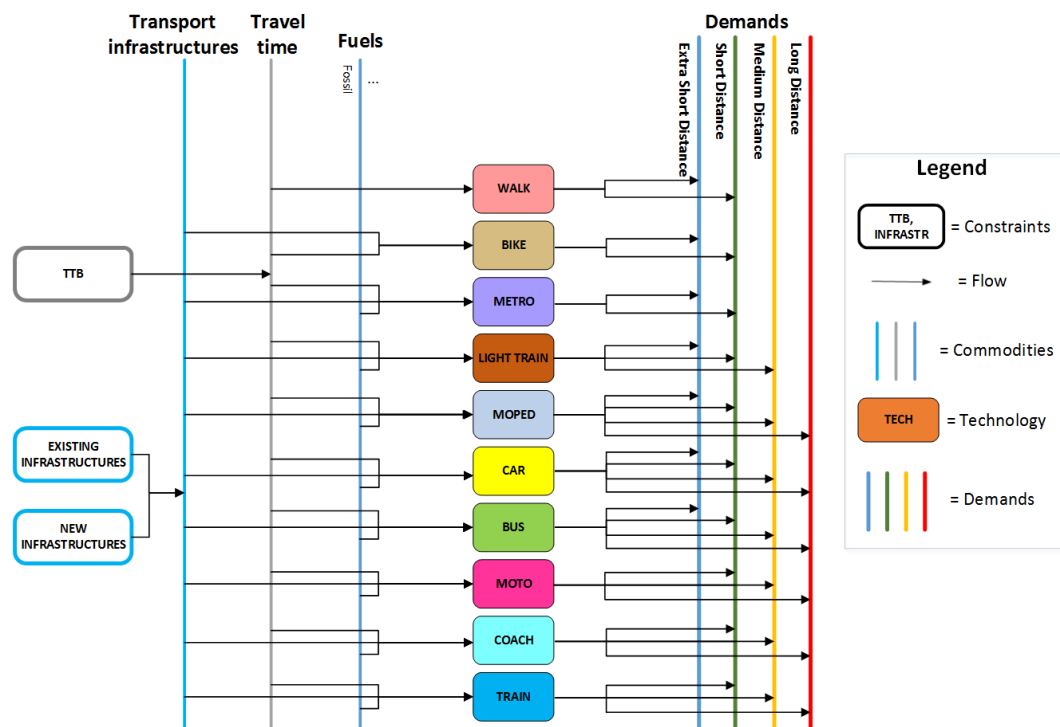


Figure 7.1: Structure of the inland passenger transport sector in TIMES-DKMS for incorporating modal shift

TIMES-DKMS outputs the least-cost decarbonisation pathway that meets all the technical, environmental, policy and resource availability constraints included in the model. However, the description of the private car sector in TIMES-DKMS is purely techno-economic, and does not account for heterogeneity within the private car market, thus suggesting a solution that may not be technically feasible (see Chapter 4). The consumer choice model and stock simulation model for the car sector developed in Chapter 6 are used to check the feasibility of the vehicle portfolio deployment pattern identified by TIMES-DKMS.

7.2.2 Danish Car Stock Model – DCSM

The Danish Car Stock Model (DCSM) has two core components; a socio-economic consumer choice model and a techno-economic CarSTOCK model. Both are integrated to provide a simulation model framework with a behaviour representation to compliment, assess, and add value to the TIMES-DKMS results. A brief summary of the structure and operability of both models is provided in this section.

7.2.2.1 Consumer Choice Model

The consumer choice model estimates the influence of various policies on the Danish private vehicle market. Heterogeneity of private vehicle preferences are accounted by splitting transport users into 18 segments, divided geographically (urban/rural), by driving profile (Modest Driver, Average Driver, Frequent Driver) and by adoption propensity (Early Adopter, Early Majority, Late Majority), inspired by McCollum et al. (2016) and Wilson et al. (2014). Five technologies split into three categories are represented in the model – petrol internal combustion engine (ICE), diesel ICE, natural gas (NG) ICE, BEV and PHEV disaggregated into the classes small, medium, and large (for ICEs, based off engine size) and into short, medium, and long range for BEVs (<125km, 125-175km, >175km respectively).

The consumer choice model of the private transport sector for Denmark includes the tangible costs faced by the consumers (such as investment cost, and vehicle-related taxes) along with a monetised representation of the intangible costs related to model availability, namely risk related disutility, range anxiety, and refuelling infrastructure. A detailed description of the market segmentation and of the tangible and intangible costs for Denmark is provided in the preceding chapter of this thesis. Policy measures can be integrated into the model by either varying the tangible costs, such as derogating vehicle registration tax (VRT), or by manipulating the variables affecting intangible costs, such as model availability.

7.2.2.2 CarSTOCK Model

The consumer choice model alone cannot determine the impact of policy measures on aggregate stock. To account for this, the CarSTOCK model is employed, using the outputs of the consumer choice model to create stock projections. The CarSTOCK model is a bottom-up techno-economic model, which uses a technically detailed representation of the transport sector to provide a full representative breakdown of stock, energy consumption, activity, and WTW CO₂ emissions in Denmark, thus determining the net effect of policy measures.

The CarSTOCK model draws upon detailed Danish statistics (FDM, 2017a), relating to the composition of private car sales, average mileage, efficiency, and life-time of vehicles with a disaggregation of vintage, fuel type and engine size (vehicle range in the case of BEVs). Using these inputs, it determines the long-term evolution of the private car stock, energy use and related CO₂ emissions to 2050 based off the ASIF methodology developed by Schipper et al. (2000). In brief, total private transport related CO₂ emissions are calculated as a sum of the product of vehicle activity (A), private car stock (S), energy intensity (I), and emission factors (F) for fuel type (f) and vintage (v).

Projections of total activity and total stock are calculated endogenously within the CarSTOCK model, using gross national product (GNP) and fuel prices, linked with literature based elasticities of demand, as drivers.

7.2.3 Multi-Model Approach

Integrating models has become an increasingly common approach in the field of energy modelling (Lanz and Rausch, 2011, Merven et al., 2012, Mulholland et al., 2017, Schäfer and Jacoby, 2005) and combining different modelling approaches can take advantage of the strengths of individual methodologies and add value and insight to individual approaches, as already identified in Chapter 4. In the modelling framework used here, TIMES-DKMS first determines the optimal technology investments to meet the exogenous end-use demands at the least overall systems costs. Then, DCSM is employed to check the technical feasibility of the solution obtained with TIMES-DKMS for the private passenger transport sector. If the solution is not feasible, capacity constraints are added in TIMES-DK to comply with the DCSM projections. A new solution is obtained with TIMES-DKMS, which is again verified in DCSM. Data exchange between the two modelling frameworks is iterated until there is convergence between the two model results. The cross-communication between the models is shown in Figure 7.2. This process mimics the approach adopted in Chapters 3 and 4, with the added inclusion of socio-economic modelling methods, i.e., the time travel budget in TIMES-DKMS, and the consumer choice model in DCSM.

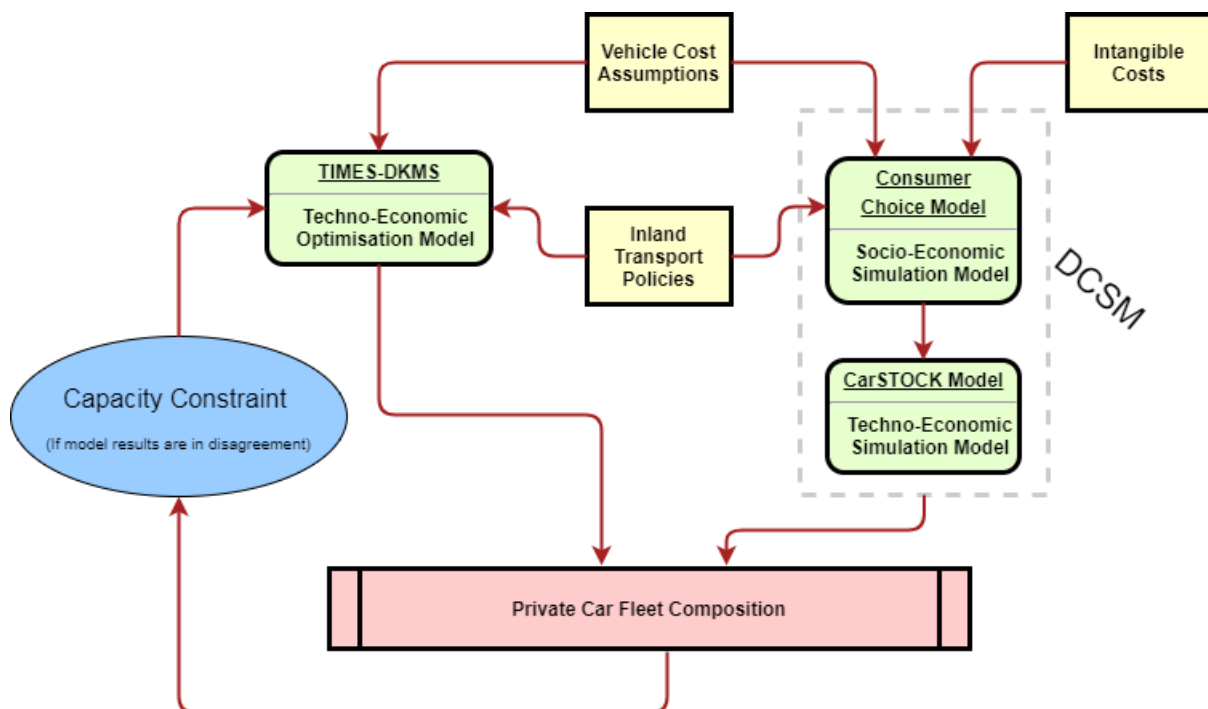


Figure 7.2: Model Integration between TIMES-DKMS and DCSM

In order to ensure consistency within the model framework developed, the private vehicle costs in TIMES-DKMS and DCSM were harmonised for 2015 as shown in Figure 7.3. There is an additional cost for road infrastructure cost in TIMES-DKMS which is omitted from Figure 7.3, as it is identical for all car technologies. Upon the inclusion of intangible costs in DCSM, the merit order of the car technologies changes with respect to an analysis limited to tangible costs. This reflection suggests that DCSM offers a more comprehensive view on the characteristics of cars accounted by consumers. Therefore, the multi-model approach employed in this study benefits from the models' respective strengths: the holistic representation of the integrated Danish energy system and the behaviourally detailed insight of the Danish car consumer choice.

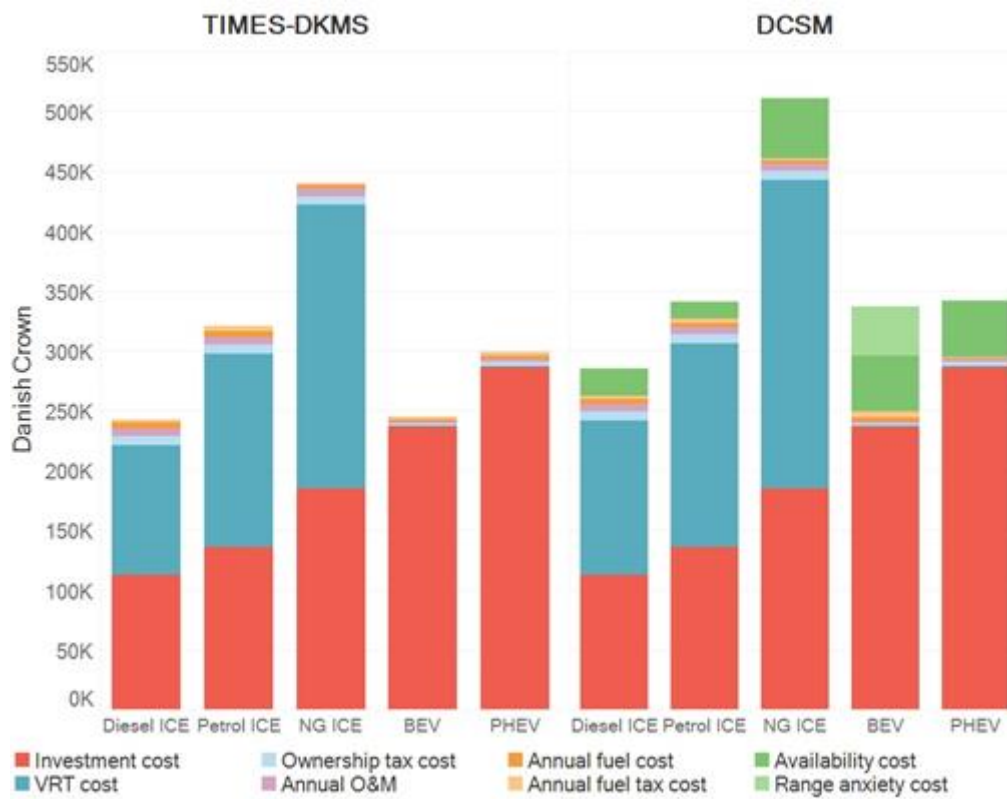


Figure 7.3: Comparison of tangible and intangible costs in 2015 in TIMES-DKMS and DCSM

7.2.4 Carbon Budget for Denmark

There has been no conformity on the distribution of global carbon budgets amongst nations to date. This study allocates a carbon budget for Denmark based on population ('equity') and emissions ('inertia'), taken from a method proposed by Raupach et al. (2014), which uses Equation 7.1 to calculate Denmark's carbon budget share, s :

$$s_j = 0.5 \frac{f_j}{F} + 0.5 \frac{p_j}{P} \quad (7.1)$$

This method calculates the emissions budget share for a region j as a combination of the share of regional emissions f_j to global emissions F and of regional population p_j to global population P .

To establish the carbon budget for Denmark, firstly the global carbon budgets required to limit global temperature rise between a range of 1.5°C to 4°C with varying probabilities of achievement were taken from the 5th Assessment Report by IPCC (2014a), which uses a base year of 2011. Denmark's national share was then calculated using emission data sourced from the United Nations' (UN) CO₂ emissions portfolio (UN, 2017) and population data was sourced from the UN's World Population Prospects (UN, 2016), which amounted to an allocated share of 0.102% of the global carbon budget using Equation 7.1. This national budget was brought up to a base year of 2015 by accounting for Danish national emissions between 2011 to 2015 taken from UN (2017). Land use and land use change and forestry (LULUCF) related emissions were subtracted using data from CDIAC (2016), finally resulting in the range of carbon budgets presented in Table 7.1.

Table 7.1: Carbon budgets for the Danish energy system from 2015 corresponding to different levels of global temperature rise and levels of confidence, expressed in MtCO₂eq

Temperature rise/Confidence level	66%	50%	33%
4°C Target	3,438	4,031	4,562
3.5°C Target	2,754	3,265	3,737
3°C Target	2,090	2,499	2,958
2.5°C Target	1,375	1,733	2,065
2°C Target	660	967	1,171
1.5°C Target	48	201	507

7.2.5 Scenario Definition

In this study, an analysis is performed to understand the potential reduction of GHG emissions in Denmark enabled by alternative developments for the VRT, the fuel tax and from banning the sale of ICE vehicles enforced in different years. In Denmark, the current legislation applies a set of taxes on passenger motor vehicles: a *VRT* proportional to the investment cost of the vehicle and based on the fuel efficiency, to be paid upon purchase; a *fuel efficiency tax*, paid twice a year by gasoline, diesel and hybrid vehicles; a *weight tax*, paid twice a year by all vehicles and proportional to the weight of the vehicle. As several European countries have established revenue-neutral feebate schemes, i.e., a combination of rebates awarded to purchasers of low carbon emission vehicles and fees charged to purchasers of less efficient vehicles, in the *VRT* scenario the effect of the introduction of a feebate

scheme derogating the VRT for BEVs and PHEVs from 2020 onwards is assessed. Furthermore, taxes are applied to the purchase of transport fuels - in the *Fuel Tax* scenario, the tax on electricity used in transport is lifted from 2020 onwards, while keeping all other fuel taxes constant. In the *Fuel Tax and VRT* scenario, the combined effect of the VRT derogation with removing the fuel tax on electricity from 2020 is examined. There is also an ongoing discussion regarding the ban on the sales of ICE vehicles. While this measure has not been proposed in Denmark yet, several car manufacturers have announced their willingness to offer more models of EVs in the near future (IEA, 2017c) which justifies the interest in analysing the effects of a ban on ICE cars in 2025, 2030, 2035 and 2040.

The policy scenarios analysed in this study are presented and described in Table 7.2. Since Denmark is aiming at becoming completely independent from fossil fuels by 2050 (DEA, 2015), all the policy scenarios include a decarbonisation constraint in 2050, placed on all sectors represented in TIMES-DKMS, with the exception of inland transport, for which the policies under assessment are the only option to reach the decarbonisation. Moreover, medium-term targets complying with the European objective of achieving a minimum of 10% renewable energy share in transport by 2020 and a 39% GHG emission reduction in 2030 with respect to 2005 levels (European Commission, 2011) is introduced. Furthermore, the goal of achieving a minimum of 50% wind-power electricity penetration by 2020 is included (IRENA, 2013). The policy scenarios are compared against a reference scenario (*Ref*), which maintains only the short-term targets for 2020, i.e., a minimum 10% renewable energy share in transport and 50% electricity production from wind power.

Table 7.2: Description of scenarios for the policy analysis

Scenario	Description
<i>Ref</i>	Reference scenario, only 2020 targets included.
<i>Fuel Tax</i>	The tax paid on electricity used for transport, equal to 245.8 DKK/GJ in 2015, is derogated from 2020 onwards. Planned subsidies on biogas used for transport (87.2 DKK/GJ in 2015) are included until 2023.
<i>VRT</i>	The Vehicle Registration Tax (VRT), to be paid upon purchase, is proportional to the investment cost of the vehicle and based on the fuel efficiency: this is lifted for all electric, hybrid and hydrogen vehicles from 2020 onwards.
<i>ICE_Ban_2025</i>	A ban on the purchase of new ICE cars is introduced from the year 2025.
<i>ICE_Ban_2030</i>	A ban on the purchase of new ICE cars is introduced from the year 2030.
<i>ICE_Ban_2035</i>	A ban on the purchase of new ICE cars is introduced from the year 2035.
<i>ICE_Ban_2040</i>	A ban on the purchase of new ICE cars is introduced from the year 2040.
<i>Fuel Tax and VRT</i>	Combination of the scenarios Fuel Tax and VRT.

7.3. Results

7.3.1 Policies Contribution to the Decarbonisation of the Danish Inland Transport Sector

The evolution of the Danish car stock and car technologies across the modelling horizon of TIMES-DKMS for the policies identified in Table 7.2 is shown in Figure 7.4, presenting the final iteration between TIMES-DKMS and DCSM. The *Ref* scenario has a minor penetration of alternative fuelled vehicles (AFV), which represent 2.6% of the total car stock in 2050. The regulatory policy scenarios each boost the penetration of EVs with varying degrees of effectiveness. The derogation of the tax on electricity for transport does not foster a strong penetration of EVs, while a derogation of the VRT on EVs enables a significant electrification of the car stock by 2050 (29.8% of car stock). The combined effect of fuel tax and VRT derogation accelerates the process of electrification of the car stock, which becomes almost half electric (49.9%) in 2050. Setting a ban on the sale/importation of vehicles run solely by an ICE strongly promotes the total electrification of the car stock. In the *ICE_Ban_2040* scenario, 93.3% of the stock is electric in 2050, while in *ICE_Ban_2035* scenario the entire stock becomes electric in 2050. The complete electrification of the car stock is anticipated by 2045 in the *ICE_Ban_2030* scenario and by 2040 for *ICE_Ban_2025*. Among EVs, PHEV technology only reaches a significant share of the total stock in the VRT scenario (6.2% in 2050), which demonstrates that the major barrier to the wide deployment of this technology is its high investment cost. In all the other scenarios, PHEVs are mostly regarded as a transition technology, reaching a maximum penetration around 2020, afterwards outclassed by BEVs due to their relatively lower investment cost.

In most policy scenarios, modal shift creates a reduction in the car stock over the period 2020 – 2030. This occurs due to the increase in the average cost of ICE vehicles, to fulfil the more stringent EU fuel standards (see Chapter 6 for a further description of cost assumptions), concurrent with high short-term AFV costs which have not decreased enough as to become a widely accepted technology, prompting a modal shift to public bus, which is a cheaper option (see Figure 7.5). After 2035, BEVs achieve a significant cost reduction due to the decrease in battery production costs and cars gain a higher modal share at the expense of public bus. In 2050, across all policy scenarios, bike, coach, metro, S-train and train increase their market share with respect to 2010, at the expense of transport via bus, car, 2-wheeler and walk. In particular, bike and coach transport experience the highest increment of use with respect to 2010, increasing by approximately 2.5 and 2.9 times relative to 2015 respectively across all policy scenarios.

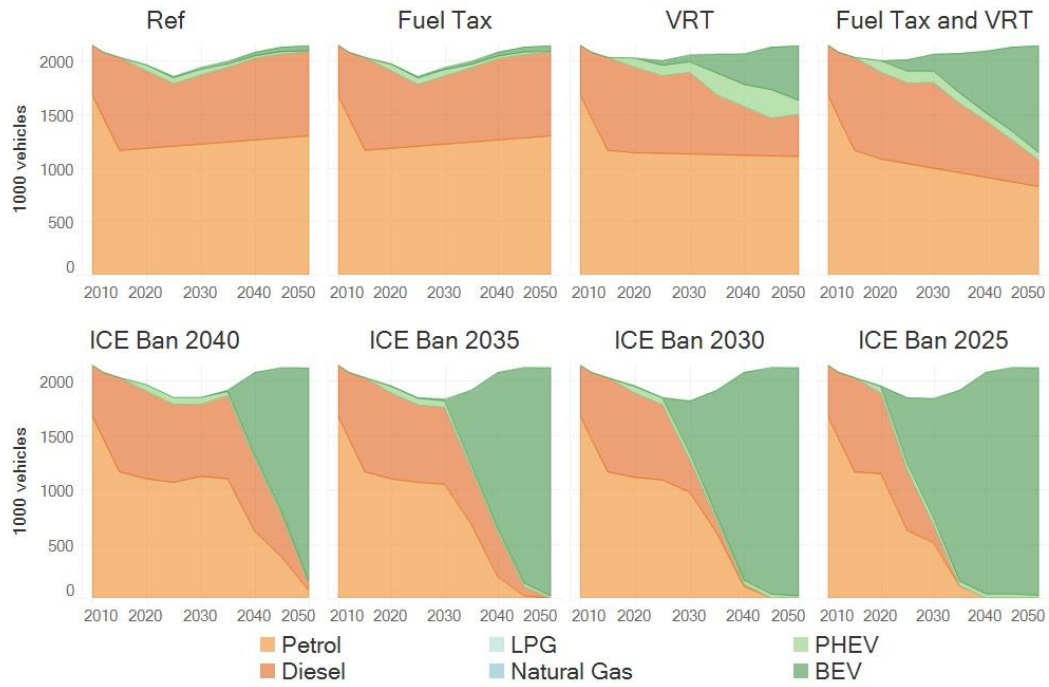


Figure 7.4: Evolution of the car stock and car technologies in time across scenarios in TIMES-DKMS

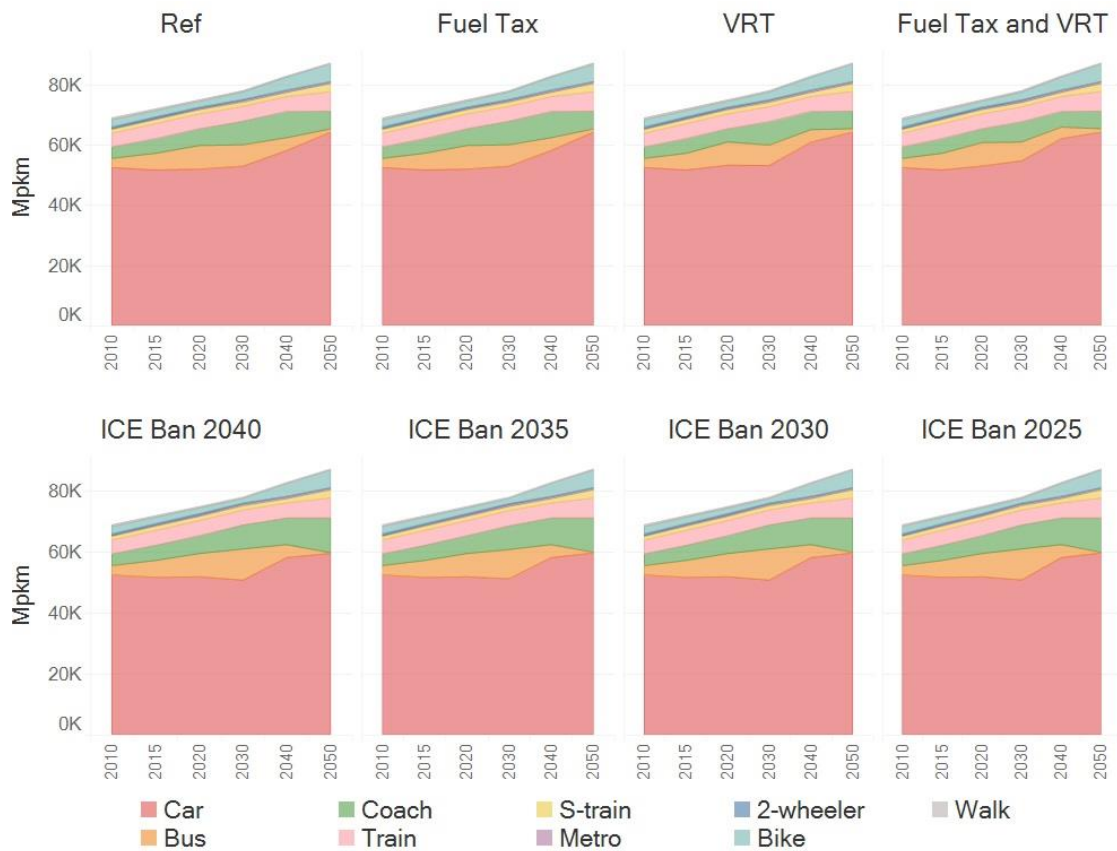


Figure 7.5: Modal shares across scenarios in TIMES-DKMS

Fuel consumption from the inland passenger transport sector for the *Ref* scenario is presented in Figure 7.6. The consumption of diesel and bio-diesel combined first increases out to 2020, and then decreases by 2050 following improvements in vehicle fuel-economy and fuel switching (predominantly to electricity). The share of blended bio-diesel gradually increases to 72% in 2050. The consumption of gasoline and bio-ethanol decreases over time, while the share of bio-ethanol in the blend increases from 6% in 2015 to 45% in 2050. Moreover, electricity acquires a higher importance as a transport fuel, constituting 5.3% of the total fuel consumption share in 2050. The drop-in fuel consumption in 2030 is a consequence of multiple factors: a shift away from cars towards bus travel (characterised by a lower relative energy-intensity), an electrification of the car stock (which are significantly more efficient than ICEs) and an overall improvement in vehicle efficiency.

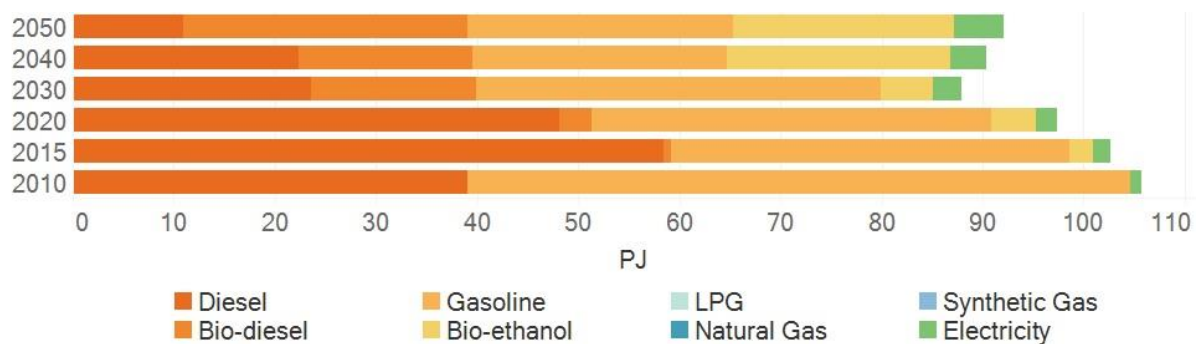


Figure 7.6: Fuel consumption from inland transport in *Ref* scenario

Inland passenger transport related fuel consumption varies across each scenario due to varieties in modal shares and technology shares within the car stock. This variance is presented in Figure 7.7, whereby the change in fuel consumption for all scenarios relative to the reference is shown. All the policy scenarios, with the exception of the *Fuel_Tax* scenario, have a reduction in total fuel consumptions in 2050 with respect to the *Ref* scenario. Placing a ban on ICE vehicles encourages the reduction in fuel consumption due to the switch to electric vehicles (EVs), which have a significantly higher fuel economy than their ICE counterpart. It should also be noted that the private car sector has a major impact on total fuel consumption from the perspective of the inland passenger transport sector, shown in the similarities between the variations in car stock (Figure 7.4) and fuel consumption (Figure 7.7).

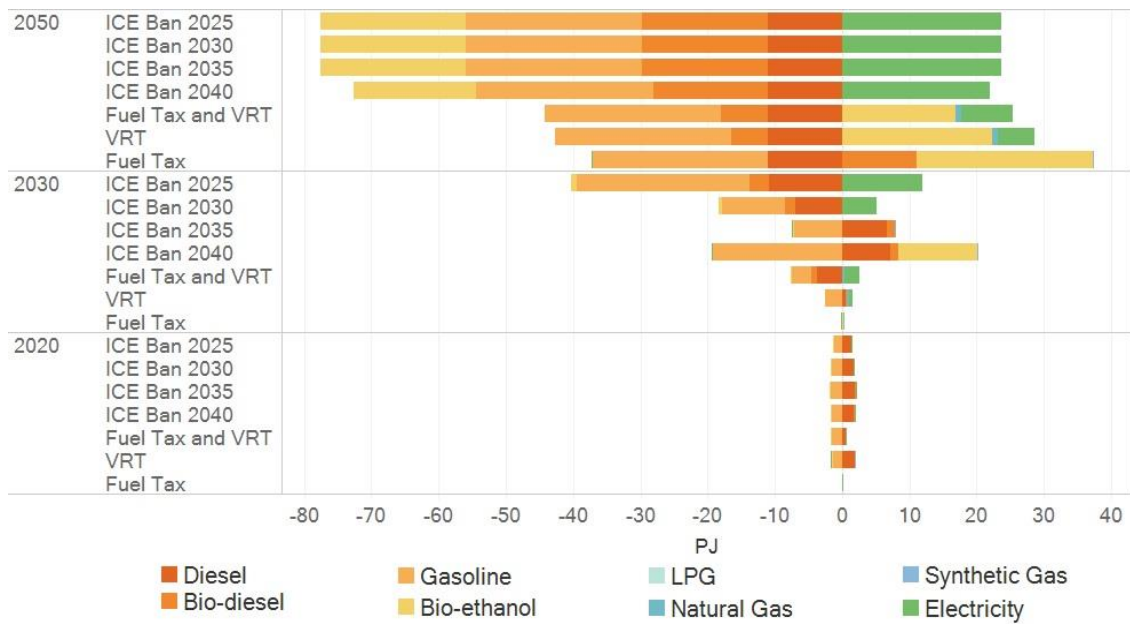


Figure 7.7: Difference in fuel consumption from inland transport across policy scenarios with respect to the Ref scenario

Figure 7.8 illustrates the cumulative GHG emissions from the inland passenger transport sector for all scenarios. The annual GHG emissions from inland passenger transport undergo a significant decrease over time across all scenarios, including the *Ref* scenario. Inland passenger transport emissions in 2050 are reduced by over 60% in the reference with respect to 2010 due to a penetration of biofuels, EVs, and increases in the average efficiency of vehicles. These reductions are made despite the overall increase of transport activity over the same period. The further implementation of transport policies enables the achievement of more ambitious decarbonisation targets. The inland passenger transport sector is completely decarbonised by 2050 in the *Fuel_Tax* scenario and all scenarios which instigate an ICE ban. The greatest cumulative reduction in GHG emissions is achieved through an early ban placed on vehicles fuelled solely by an ICE (in 2025 and in 2030), while taxation focused policies have a similar effect to that of later bans (in 2035 and 2040).

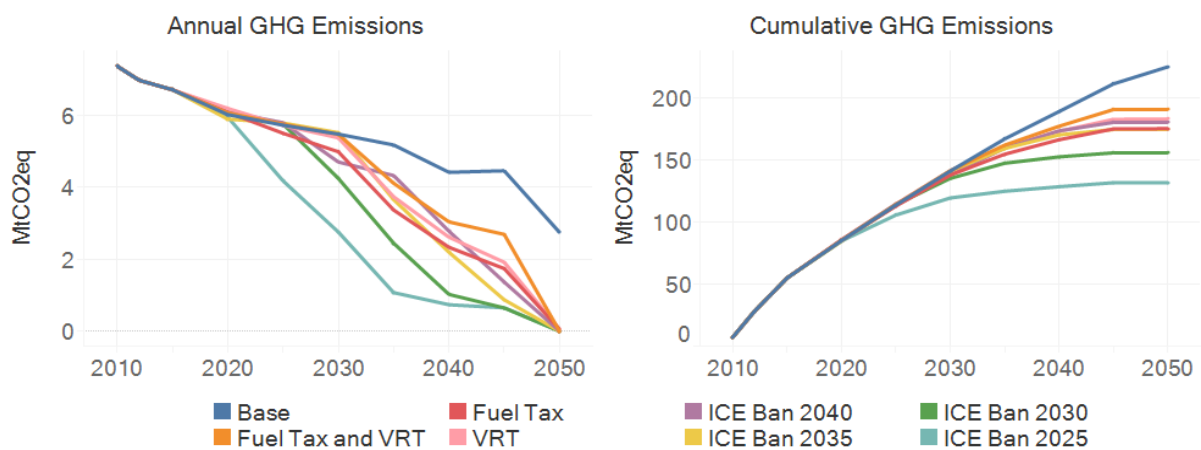


Figure 7.8: Cumulative GHG emissions from the inland Danish transport sector

Figure 7.9 extends the focus of the analysis from inland transport to the entire Danish energy system, showing the cumulative GHG emissions produced by the entire Danish energy system over the modelled time horizon. In the *Ref* scenario, the cumulative GHG emissions diverge from the policy scenarios from 2025, and the steepness of cumulative GHG emissions increases after 2030 due to the adoption of coal-fired plants for power generation. In the transport policy scenarios, GHG emissions gradually reduce over time, in order to comply with the Danish environmental target of becoming fossil-free by 2050.²

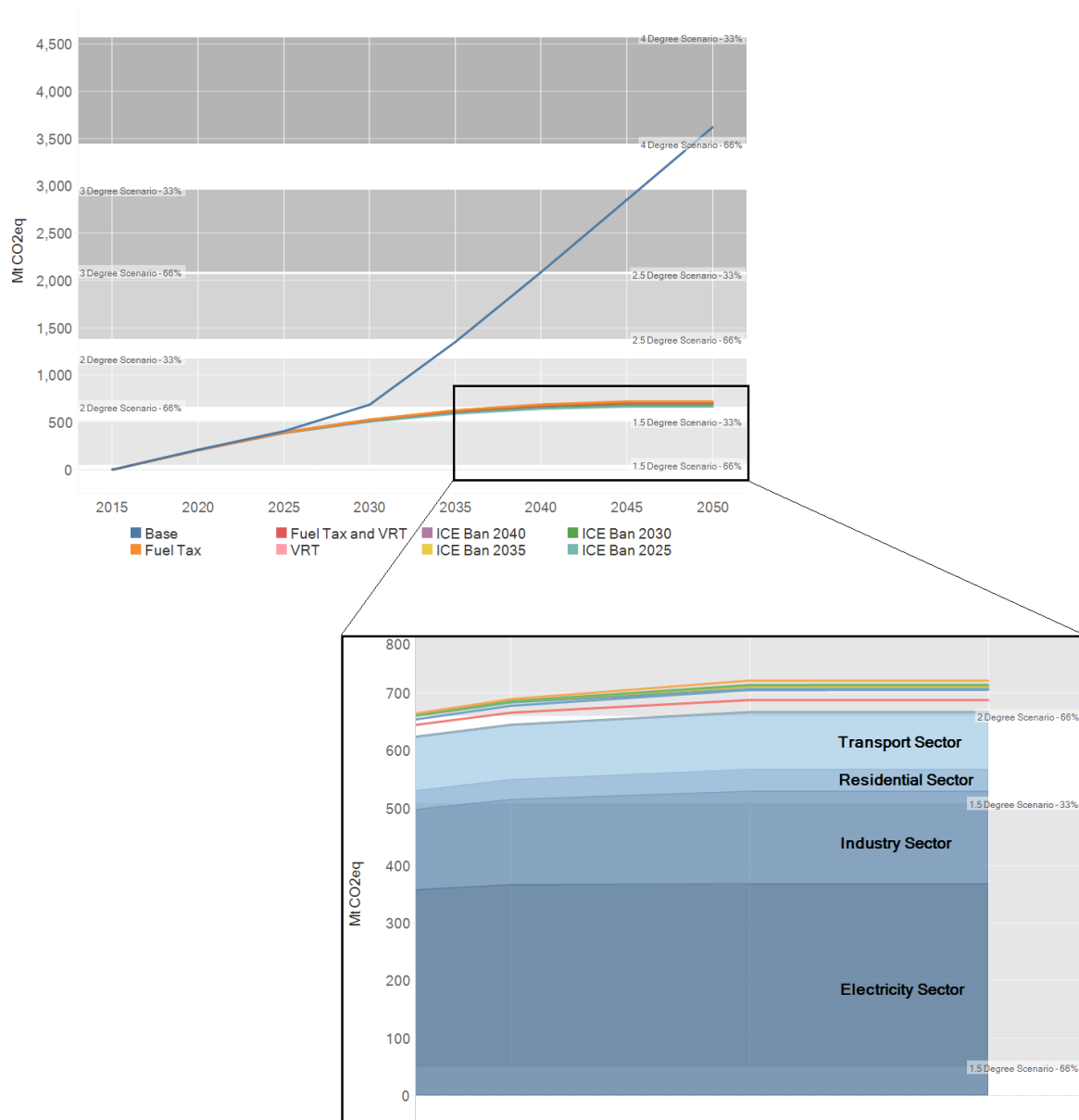


Figure 7.9: Cumulative GHG emissions from the entire Danish energy system

² The policy scenarios set a limit on GHG emissions from all sectors except inland transport, for which the policies tested are the only measure promoting the decarbonisation

Granted a fossil-free energy system is achieved in all sectors excluding inland passenger transport, the policy scenarios modelled indicate that cumulative GHG emissions from the entire Danish energy system in 2050 are in line with a national contribution to an increase in global temperatures of 1.75-2°C, excluding the possibility of negative emissions in the second half of the century, e.g. reforestation and bio-energy with carbon capture and storage (BECCS) (IEA, 2011).

Finally, the effect of policies on the tax revenue is provided in Figure 7.10, showing that *Fuel Tax and VRT* implies the highest loss of revenue for the exchequer. The 6.2% reduction for *Fuel Tax and VRT* is explained by the uptake of BEV and PHEV from 2020, upon which no VRT and tax on electricity consumption are imposed. On the other hand, the *ICE_Ban* scenarios benefit the tax revenues, due to the penetration of taxed AFV when their investment costs have not dropped yet.

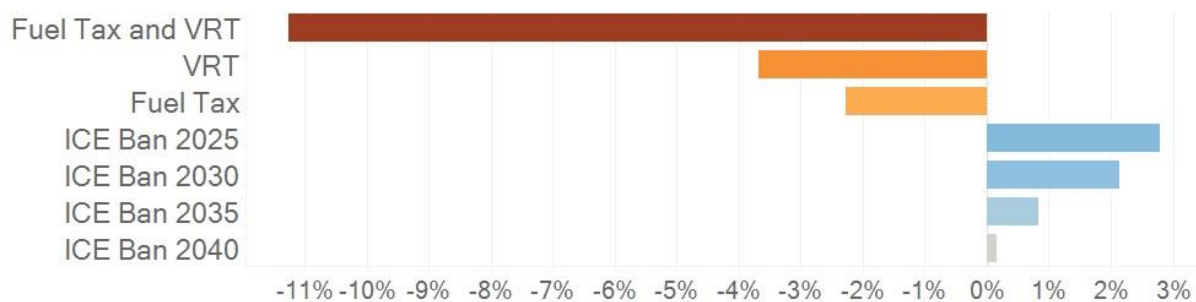


Figure 7.10: Actualized cumulative change in tax revenue with respect to the Ref scenario

7.4. Discussion

This study has analysed a range of regulatory measures focused on the inland passenger transport sector while simultaneously decarbonising the rest of the energy system at least-cost. A central focus has been given to the potential of these measures in minimising cumulative GHG emissions to adhere to national carbon budgets capable of contributing towards a limit in the rise of global temperatures. Nonetheless, while evaluating the potential outcome of transport policies, it is important to consider not only their effectiveness, but also their efficiency, which is evaluated as difference in actualized tax revenue with respect to the *Ref* scenario. Although from an environmental and tax revenue perspective, the *ICE_Ban_2025* is the most effective of all policies analysed, it is important to consider the different degrees of feasibility of policy instigation, stemming from their different timing, method of implementation, and public acceptability. Changes to taxation schemes require several Government consultations while the introduction of a ban of ICEs presents a challenge in terms of negotiations (on timing and exceptions) with the automotive industry, let alone the preferences of consumers. This proves particularly difficult for Denmark as

there are no vehicle manufacturers based in the country, however, some countries and cities around the world have already announced ambitions to ban the sale of diesel and petrol cars: France and United Kingdom from 2040, India from 2030 and Norway by 2025 (Petrof, 2017, Chrisafis and Vaughan, 2017).

Measures affecting modal shift, e.g., investments in public transport and bike infrastructure (Tattini et al., 2017b), or the promotion of ride-sharing through high-occupancy vehicle (HOV) lanes (Enoch and Taylor, 2006) have not been addressed. Other physical policies closely related to urban planning and land use patterns, such as parking reforms, dedicated bus lanes, and road pricing, would require a more geographically detailed model framework. The effect of soft policies addressing e.g., eco-driving campaigns and speed limit enforcements (Elvik and Ramjerdi, 2014), still needs to be assessed.

Although the model framework adopted represents an improvement in traditional techno-economic optimization energy system models by integrating a socio-economic and techno-economic simulation model framework, there are still some limitations that future research may address. A first limitation lies with the fact that the results provided by TIMES-DKMS are relatively optimistic when compared to those provided by DCSM. Although the results of the two models have been iterated, the simplified representation of lifetime of cars in TIMES-DKMS is represented with difficulty; even with a ban on ICE vehicles in 2025, there would still be some ICE vehicles circulating in 2050 according to DCSM (without any incentive for early scrapping). TIMES-DKMS has a set-lifetime for all vehicles, i.e., 16 years, and does not account for the marginal stock which remains for longer than this. Besides this, DCSM assumes that the future retirement profile of cars will be identical to the one historically observed. This assumption does not consider e.g., the rise and spread of new mobility phenomena like Maas and car leasing, which are characterised by early vehicle scrapping.

This chapter has accounted for some degree of consumer representation through modelling modal shift (in TIMES-DKMS) and consumer preferences (in DCSM). Nonetheless, the representation of modal choice can be expanded upon as modal shift is evaluated only via a suitably constrained socio-economic optimisation. A possible way to overcome this shortcoming would be through integrating consumers' heterogeneity into the model, thus differentiating their travel habits, perceptions and thus preferences and determining modal shares resulting from a set of decisions taken by diverse consumers. Moreover, the level-of-service attributes characterising the modes shall go beyond

speed, to include also other relevant ones, such as waiting time, transfer time and access/egress time. The methodology of CoChin-TIMES (Bunch et al., 2015) offers an alternative for incorporating consumer choice in the private vehicle sector directly within the TIMES framework, without any need for external linkage. Finally, while this study has calculated potential national carbon budgets for Denmark to contribute towards a well-below 2°C future based on a combination of equity and inertia sharing, these budgets will not be effective unless there is global conformity on the method of allocating national and regional carbon budgets.

7.5. Conclusions

This study developed an innovative multi-model approach that integrated an optimization energy system model (TIMES-DKMS) with a simulation model of the private car sector (DCSM) to assess the influence of various regulatory policy measures on the decarbonisation of the inland passenger transport sector of Denmark. The multi-model approach was carried out using a soft-linking approach between the two models, whereby the same policies were run in both models and capacity constraints were introduced in TIMES-DKMS to converge the private car stock results between the models and verifying the feasibility of the private vehicle deployment pattern suggested by TIMES-DKMS. The multi-model approach developed combines the strengths of both modelling methods and provides a greater degree of consumer realism to the analysis of the private car sector. The potential contribution of seven policy measures towards the decarbonisation of the Danish inland passenger transport sector was analysed in Section 7.4. This analysis revealed that a ban on the sale of cars powered solely by an ICE in 2025 enables the deepest cut in GHG emissions of all policies modelled and generates the highest tax revenue for the exchequer. Regulatory measures focused on the derogation of tax have a lower relative effect on cumulative GHG emissions reduction and have a net negative impact on tax revenue when compared against a reference baseline. Nonetheless, all scenarios have a significant level of decarbonisation by 2050, with a complete decarbonisation of inland passenger transport in all scenarios where a ban on the sale of ICEs was instigated, and a greater than 90% reduction relative to 2015 in policies focused on tax derogation. Moreover, a broader analysis on the entire energy system revealed that even a total derogation of VRT and fuel tax for AFV and an early ban on the sale of ICE vehicles would not contribute to maintain the increase of global temperature limited to 1.5°C, and would be more likely in line with a 1.75°C-2°C scenario.

Chapter 8

Conclusions

The importance of evidence based energy policy for steering the world and its economic sectors away from a future dominated by fossil fuels to a future based on sustainability cannot be understated. The transport sector is no exception as the majority of road transport remains dominated by carbon-intensive petroleum-based fuels. It is primarily through policy interventions in the last decade that there has begun to be an emergence of alternative fuelled vehicles. For example, the vehicle registration tax (VRT) subsidy offered in Ireland and Denmark alleviated the resistance the uptake of electric vehicles (EV) (see Chapter 4 and Chapter 6). Furthermore, Norway has shown how felicitous policies can encourage EV adoption (Mersky et al., 2016). However, well-intentioned policy can be costly and ineffective if not informed by a sufficient evidence base underpinned by a minimum level of technical and societal detail. This thesis has shown how a combination of techno-economic and socio-economic models utilised in tandem with optimisation and simulation modelling methods can support informed climate related policy decisions for the transport sector, at the national and international level.

The original aim of this thesis was to improve the robustness of models that inform policy decisions for the road transport sector, and this conclusion stands as a summary of how this was achieved. This aim can be further broken down into the 6 research questions (RQs) initially posed by this thesis:

- RQ 1.** *What policies can assist in a decarbonisation of road freight vehicles?*
- RQ 2.** *What policies can assist in a decarbonisation of passenger vehicles?*
- RQ 3.** *What transportation policies may adhere to a <2°C scenario?*
- RQ 4.** *What are the current state-of-the-art techno-economic transportation models?*
- RQ 5.** *What are the limitations and potential improvements of techno-economic models?*
- RQ 6.** *What are the current state-of-the-art socio-economic modelling methods, and how can these be integrated with techno-economic modelling methods?*

Each chapter within this thesis has set out to achieve one or more of these research questions by informing climate related policy through an expansion of current transportation modelling practices. This final chapter summarises the findings of this work within a policy and modelling context, and identifies areas of potential future work.

Policy

Transport specific policy can be targeted at a range of agents, varying from those located at the end use – such as the consumer - to those up-stream in the supply chain - such as fuel suppliers and vehicle manufacturers. However, the level of uncertainty for different policies across this spectrum varies. Regulation based supply-side policies, such as mandating vehicle manufacturers, can be implemented with a relatively higher level of certainty, e.g., the formal adoption of CO₂ performance standard regulations as decreed by regulation EC 443/2009 (European Parliament, 2009b) and the Zero Emission Vehicle Program adopted by the State of California (CARB, 2009) – though compliance still cannot be taken for granted. However, market based consumer-focused policies such as those aimed at incentivising consumers to switch to alternative modes of transport or to purchase alternative fuelled vehicles may be met with a diverse response due to the heterogeneity of the transportation market. For example, the VRT subsidies for Ireland and Denmark have assisted in the uptake of EVs, although this uptake has varied suggesting that it is difficult to determine the exact effect of a single grant scheme on changes in market share. The policies presented in this section are aimed at a variety of agents in the transport sector, with the eventual inclusion of socio-economic modelling methods as a means of improving the certainty surrounding consumer specific policies.

RQ 1 – Road Freight Decarbonisation Policies

Global transport policy is addressed in Chapter 2, with a focus given to the road freight sector, which accounted for one fifth of global oil consumption and one third of road transport related well-to-wheel (WTW) greenhouse gas (GHG) emissions in 2015 (IEA, 2017b). This chapter identified the lack of national focus given to the trucking sector, especially when compared to the the backdrop of private car focused policy. For example, of the current 133 submitted Intended Nationally Determined Contributions (INDCs), only 13% mention freight while 61% mention passenger transport (Gota, 2016). The low level of focus on freight transport is remarkable, considering the recent increases in road freight activity – in its extremity, amounting to 30-fold increases for certain regions over the period 1975 – 2015. As a means of curbing the growth rate of road freight vehicles and reducing the emissions intensity of related activity, policy measures aimed at manufacturers and freight operators may sufficiently reduce GHG emissions in the long term to 2050. This chapter

concludes with the finding that instigating fuel economy standards on truck manufacturers, differentiating taxes on vehicle purchases, encouraging freight systemic improvements, and supporting the deployment of alternative fuelled trucks have the combined potential to contribute to a 60% reduction of global truck related WTW CO₂ emissions by 2050, over a 2015 baseline. In the absence of any extra policy, these emissions can be expected to rise by 56% over the same period, which includes the ambitions of the INDCs laid out by the COP21 signatories.

Chapter 3 retained a focus on the road freight sector, with a localised emphasis on a national case study of Ireland, in contrast to the global focus of the preceding chapter. The policy and technical outcomes of this chapter differ from that of Chapter 2 following a change in the modelling framework used (simulation modelling in Chapter 2, and a hybrid of optimisation and simulation modelling in Chapter 3). In brief, this chapter concludes that an optimal decarbonisation of the Irish energy system (80% CO₂ reduction by 2050 relative to 1990) could be achieved through a complete decarbonisation of light commercial vehicles (LCVs), primarily through the emergence of biogas as a fuel source. A change in the taxation system of LCVs – i.e., basing the tax payable on CO₂ emissions rather than laden weight as it currently stands – contributes towards this optimal solution. Most importantly, instigating a ban on the sale of LCVs powered by the internal combustion engine (ICE) in 2030 would be sufficient to incentivise a full shift of the LCV stock towards compressed natural gas (CNG) vehicles by 2050. This chapter also examines the resource of indigenous feedstock to fuel these vehicles on biogas, and concludes that there is sufficient availability in the form of excess grass silage to fuel the LCV fleet, provided the appropriate number of biogas plants are built, i.e., 248 plants with a capacity of 50,000 t/year. In contrast to the preceding chapter, where an emphasis was given to the prevalence of electric LCVs based on ‘what-if’ analysis based on expert judgement, when considered at a national level and optimised from the energy planner’s perspective, CNG LCVs were found to be a more effective solution to decarbonisation.

RQ 2 – Private Car Specific Decarbonisation Policies

Chapter 4 uses the same modelling methodology as Chapter 3, with a focus shifted to the private car sector in Ireland, whereby the Irish TIMES techno-economic optimisation model is soft-linked with the CarSTOCK techno-economic sectoral simulation model. This chapter employs an ex-post and ex-ante approach to identify specific policy measures which are in line with an 80% CO₂ reduction scenario. The cost-optimal solution calculated by the Irish TIMES model determines the need for the full electrification of the private car sector to comply with this decarbonisation in Ireland. However, the most ambitious policies created in the CarSTOCK model fail to adhere to the vision outlined by

the TIMES model. A combination of policies targeted towards fuel suppliers, vehicle manufacturers, and consumers has the potential to reduce emissions in the private car sector by 90% over the period 2015 – 2050. These policies consist of increasing the Irish Biofuel Obligation Scheme to 10.13%, up from its current value of 8.695% (fuel supplier specific policy), increasing the European vehicle standards to 75gCO₂/km beyond the currently imposed target of 95gCO₂/km (manufacturer specific policy) and offering further grant incentives to consumers for the purchasing of EVs (consumer specific policy). One limitation to this study is the uncertainty surrounding the effectiveness of grant schemes made available to the consumer – for this study, a simple consumer choice model was created whereby the intangible costs faced by the consumer were reduced iteratively to better understand the effect on market share.

Chapter 5 and Chapter 6 aim to combat this uncertainty through the review and adoption of socio-economic modelling methods respectively. A detailed consumer choice model was developed using the inputs of tangible costs (such as investment cost, fuel, operation and maintenance costs) and intangible costs (such as model availability, range anxiety, refuelling infrastructure, risk related disutility). This allows for the formation of policies targeted at reducing either the tangible or intangible costs faced by consumers of private cars in both Denmark and Ireland, while concurrently determining the cost faced by the exchequer in terms of tax foregone from the State incentivisation of battery electric vehicles (BEVs) and plug in hybrid electric vehicles (PHEVs). This chapter concludes that increasing the number of models of BEVs and PHEVs available for sale strongly influences the promotion of their uptake, although policy in this vein would be hard to implement, as both Ireland and Denmark are technology ‘takers’ rather than ‘makers’. There are, however, policies within the control of these countries capable of long term decarbonisation of the private transport sector. For example, banning the sale of ICEs in 2030 results in a reduction in private car associated WTW CO₂ emissions amounting to 69.5% in Ireland and 76.7% in Denmark, according to the consumer choice model linked to the CarSTOCK model. A high penetration of BEVs and PHEVs was achieved in both countries without the banning of ICE vehicles, through the derogation of VRT, VAT, circulation tax, and offering free charging for BEVs and PHEVs, amounting to a market share of 96% for BEV and PHEV combined in Ireland in 2050, and 84% in Denmark. However, these measures come at a cost of tax foregone of €2.1 billion¹ in Ireland and €4.3 billion in Denmark in 2050, relative to the same year in a reference scenario. This is considerably higher than the cost of banning ICEs, amounting to €169.7 million in Ireland and €433.8 million in Denmark in tax foregone by 2050.

¹ All monetary figures are in 2015€

RQ 3 – Transport Policies to go Well-Below 2°C

Chapter 7 proposed a range of carbon budgets for Denmark capable of limiting global temperature rise to between 1.5°C and 4°C, based on the equity and inertia sharing principles, and analysed how transport policy might assist in adhering to these budgets. Banning the sale of ICE vehicles in 2025 was found to be the most effective policy measure in curbing GHG emissions. However, this policy measure, alongside achievement of the currently proposed Danish energy-related target of becoming fossil fuel free by 2050, was found to not succeed in contributing towards limiting the increase of global temperature limited to 1.5°C, and was more in line with a 1.75°C – 2°C rise. Under a business as usual scenario, the cumulative carbon emissions amounted to a contribution in line with a 4°C rise. In a broader sense, there is a need for conformity in national carbon budgets, and in the absence of any effort-sharing rules we are presented with a complication in adhering to global carbon budgets, which are still contentious (Millar et al., 2017).

Modelling

The formation of the policy concluded by this thesis has relied on the support of modelling with a detailed depiction of technical and societal variables. To provide strength to these policy recommendations, this thesis has reviewed, drawn upon, and developed state-of-the-art energy transportation models by utilising a variety of modelling frameworks (techno-economic and socio-economic), modelling methods (optimisation and simulation) with a diverse geographic focus. Policy outputs can vary dependent on the mix of these parameters, as seen from the preceding section, with a summary presented in Table 8.1 below. The variety in these modelling parameters is discussed in the remainder of this section.

Table 8.1: Thesis chapter summary

	Modelling Framework	Modelling Method	Geographical Scope
Chapter 2 – Global Freight	Techno-Economic	Simulation	Global
Chapter 3 – National Freight	Techno-Economic	Optimisation + Simulation	Ireland
Chapter 4 – National Private Cars	Techno-Economic	Optimisation + Simulation	Ireland
Chapter 5 – Behaviour Review	Socio-Economic	N/A	Global
Chapter 6 – Consumer Choice	Techno-Economic + Socio Economic	Simulation	Ireland + Denmark
Chapter 7 – Below 2 Degrees	Techno-Economic + Socio Economic	Optimisation + Simulation	Denmark

RQ 4 – Analysis of Techno-Economic Transport Models

The early chapters of this thesis analyse how techno-economic models can be used to inform policy decisions. Chapter 2, for example, considered one of the state-of-the-art techno-economic energy transportation models – the IEA’s Mobility Model, a technically detailed simulation model – and developed a new method of projecting freight transport demand to provide up-to-date policy insights. This projection was created by identifying the correlation between historic activity and a range of explanatory variables, eventually conforming on a combination of GDP, fuel prices, and regional area to project road freight activity. The modelling methodology used in this chapter simulates what is technically feasible for the future of global freight by using a ‘what if’ analysis, based on expert judgement. While this approach is effective at determining what is technically feasible, it may not necessarily be considered a cost-optimal decarbonisation solution, which is introduced in the following chapter.

Chapter 3 considers another purely techno-economic approach, but with a change in geographic scope (focusing on road freight in Ireland) and a change in modelling framework (using a hybrid of an optimisation model (Irish TIMES) and a simulation model (LCV Stock Model)). The hybrid modelling approach adopted in this chapter allows for a cost-optimal decarbonisation solution to be arrived at with the backing of the LCV simulation stock model, providing an accurate depiction of light commercial vehicles in Ireland and enabling a more realistic result set than if just one of these modelling approaches were used. Chapter 4 adopts the same modelling approach, once again using a hybrid of an optimisation model (Irish TIMES) with a stock simulation model (CarSTOCK) focusing on the private car sector in Ireland, although benefitting from the addition of a simplified consumer choice model, as a way of accounting for both the tangible and intangible costs faced by consumers when choosing a vehicle to purchase.

RQ 5 – Limitations and Potential Improvements of Techno-Economic Transport Models

There are limitations associated with the use of stand-alone techno-economic models to inform policy measures, despite whether a simulation or optimisation methodology is used. In Chapter 2, a simulation method is employed with no input from other models. While this presented a view of what is technically feasible, it might not be a cost-optimal solution. An optimisation model may be used to the purpose of identifying what is cost-optimal, although the method of solving may result in unrealistic scenarios – such as the emergence of the ‘winner takes all’ phenomenon, whereby the cheapest technology available achieves full market share each year. The introduction of the hybrid

approach in Chapter 3 shows how linking a simulation model and an optimisation model may overcome the shortcoming of using a stand-alone model.

While a hybrid of simulation and optimisation provides a more realistic result set from a technical viewpoint than if only one model was used, if only a techno-economic framework is used then this approach is still susceptible to informing policies which do not account for societal behaviour. The introduction of the simplified consumer choice model in Chapter 4 shows the importance and impact of including socio-economic modelling when informing climate policy for the transportation sector, and shows how a detailed socio-economic model is needed to overcome this shortcoming of techno-economic models.

RQ 6 – Integrating Techno-Economic and Socio-Economic Modelling Methods

A review of socio-economic modelling techniques was carried out in Chapter 5 with the purpose of identifying the current methods of societal representation within transport-energy models. This thesis uses the findings of this chapter to develop existing measures of socio-economic inclusion and adapts them to be linked with techno-economic models. This adaption was carried out firstly in Chapter 6, whereby a techno-economic sectoral simulation model was linked with a socio-economic discrete consumer choice model, allowing for policies to be targeted at a heterogeneous vehicle market, thus accounting for varying propensities of adoption. Chapter 7 integrates this hybrid of techno-economic and socio-economic simulation models with an optimisation model, mimicking the approach created in Chapter 4, with greater societal representation through the use of the consumer choice model and a time travel budget. This chapter focuses on the Danish transport sector, and identifies the role of Denmark in adhering to the pledges made by COP21.

Future Work

The methods proposed in this thesis do not represent a silver bullet for a low carbon future in the transportation sector but instead are intended to provide the first step towards forming evidence-based transport focused policies. The energy system is complex, and near-impossible to model to perfect accuracy, although the development of modelling methods and techniques, such as those presented in this thesis, can assist in the initial stages of policy formation. With further development in this area comes a greater deal of accuracy, strengthening the policy measures identified by energy system models. This section identifies some areas of potential future work which may assist to this area, and that may improve modelling of the transportation sector.

This thesis builds upon current methods of socio-economic modelling within the transport sector, although the representation of societal features is relatively new in the field of transportation energy modelling and should be developed further to enable a more holistic view of the transport system. This may be possible through further use of extensive stated preference surveys targeted at key segments of consumers (such as early adopters and the late majority) to understand how best to alleviate the barriers of low-carbon vehicle adoption. Furthermore, cost-related data was found to be sparse and difficult to obtain, creating difficulty in the development of the consumer choice model developed in Chapter 6. The creation of open-source data pertaining to the costs faced by consumers would be useful for researchers who wish to improve technical representation in modelling.

The models employed by this thesis do not consider the potential technologies which may have a large impact on future driving patterns of consumers. Autonomous vehicles, for example, may create significant changes in driving behaviour in the coming decades by allowing consumers of such vehicles to live in rural areas and commute longer distances. Future research could consider the limits and potential impacts of these technologies on the energy system by running scenarios with a range of driving behaviours to understand the impact if these technologies may have if a mass market share is achieved.

Finally, this thesis largely focused on developed countries, with some inclusion of the developing world in Chapter 2, largely due to the availability of data. Low income emerging economies will have a significant role to play in the future of global transportation and in adhering to global climate targets. There is a certain need for creating a similar hybrid modelling approach as created in this thesis with a geographic focus on the developing world.

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Appendix A: Road Freight Activity Sources

Number of Observations	
	40 - 50
	20 - 39
	5 - 19
	1 - 4
	0

Table A.1: Source of data for Chapter 2

Zone	Country	Source	Total tkm	Total vkm	tkm by Truck size
ASEAN	Cambodia	World Bank			
	Lao People's Democratic Republic	Asian Development Bank			
	Myanmar	World Bank			
	Viet Nam	Asian Development Bank			
ATE	Armenia	ITF			
	Azerbaijan	ITF			
	Georgia	ITF			
	Kazakhstan	UNECE			
	Kyrgyz Republic	World Bank			
	Uzbekistan	UNECE			
China	People's Republic of China	China Statistical Yearbook, National Bureau of Statistics of China			
EU 7	Bulgaria	National Statistical Institute			
	Croatia	Croatian Bureau of Statistics			
	Cyprus	Statistical Service of Cyprus (CYSTAT)			
	Latvia	Central Statistical Bureau			
	Lithuania	Statistics Lithuania			
	Romania	National Statistical Institute			
India	India	Ministry of Road Transport and Highways			
Latin America	Argentina	Inter-American Development Bank			
	Belize	Inter-American Development Bank			
	Brazil	Inter-American Development Bank			
	Colombia	Inter-American Development Bank			
	Costa Rica	Inter-American Development Bank			
	Cuba	World Bank			
	Ecuador	Inter-American Development Bank			
	El Salvador	Inter-American Development Bank			
	Guatemala	Inter-American Development Bank			
	Honduras	Inter-American Development Bank			
	Nicaragua	Inter-American Development Bank			
	Panama	Inter-American Development Bank			
	Paraguay	Inter-American Development Bank			
	Uruguay	Inter-American Development Bank			

ODA	Afghanistan	Ministry of Transport and Civil Aviation & Other Ministries	
	Mongolia	World Bank	
	Pakistan	World Bank	
OECD Europe	Austria	Statistics Austria	
	Belgium	Statistics Belgium	
	Czech Republic	Transport Research Center	
	Denmark	Statistics Denmark	
	Estonia	Statistics Estonia	
	Finland	Statistics Finland	
	France	Ministry of Ecology, Energy, Sustainable Development and Sea	
	Germany	Kraftfahrt-Bundesamt (KBA)	
	Greece	Hellenic Statistical Authority	
	Hungary	Hungarian Central Statistical Office	
	Ireland	Central Statistics Office	
	Italy	National Statistical Institute (ISTAT)	
	Luxembourg	National Statistical Institute (STATEC)	
	Netherlands	Statistics Netherlands	
	Norway	Statistics Norway	
	Poland	Central Statistical Office	
	Portugal	National Statistical Institute (INE)	
	Slovak Republic	Statistical Office of the Slovak Republic	
	Slovenia	Statistical Office of the Republic of Slovenia	
	Spain	Ministry of Public Works and Transport	
	Sweden	The Swedish Agency for Transport Policy Analysis (Trafikanalys)	
	Switzerland	Swiss Statistics	
	United Kingdom	Department for Transport (DfT)	
OECD North America	Canada	North America's Transport Service	
	Mexico	North America's Transport Service	
	United States	U.S. Department of Transportation, Bureau of Transportation Statistics	
OECD Pacific	Australia	Department of Infrastructure and Regional Development	
	Japan	ITF	
	Korea	ITF	
	New Zealand	ITF	
OETE	Albania	ITF	
	Belarus	ITF	
	Bosnia and Herzegovina	ITF	
	Montenegro	ITF	
	Republic of Moldova	ITF	
	Serbia	ITF	
	TFYR Macedonia	ITF	
	Ukraine	ITF	
Other OECD	Chile	ITF	
Russia	Russian Federation	Federal State Statistics Service	

Appendix B: Irish TIMES model operation and input assumptions

The Irish TIMES model is a linear optimisation model with an objective function to minimise total system cost (maximizes the total discounted surplus) subject to imposed constraints. Mathematical equations describe the relationships and interaction between the many technologies, drivers and commodities in Irish TIMES. While it is tempting to think of Irish TIMES as a simple ‘merit type’ model that chooses technologies simply from the least expensive to the most expensive to meet certain demands this is an oversimplification that leads to an incorrect understanding of the model value and dynamics. The richness of the Irish TIMES model is that it optimises across all sectors of the energy system for the full horizon and thus captures the interaction between sectors. The model simultaneously solves for the least cost solution subject to emission constraints, resource potentials, technology costs, technology activity and capability to meet individual energy service demands. In this way, Irish TIMES allows technologies to compete both horizontally across different energy sectors and vertically through the time horizon of the model.

There are a large number of exogenous inputs to the Irish TIMES model. Many of these are characterizations of technology or commodity entities. There are also a number of endogenous inputs that are calculated by Irish TIMES and which are used in the final calculations for the model outputs. Some of relevant model inputs are presented in the following sections. This document serves as an overall review of these data with a further specific focus behind the private transport sector.

Technologies

In the Irish TIMES model, there are more than 1350 technologies for the supply-side and demand-side sectors of the economy. Each of these technologies has detailed technical parameters that can be changed and set by the user; some of these parameters include technology efficiency (e.g. heat rates, learning curves), technology lifetime, emission factors (CO₂ and non-CO₂) and availability. The data sources for most of these technologies are the IEA databases that were used to build the reference energy system. For Irish TIMES, the technologies parameters were all reviewed and revised, as appropriate, for Irish conditions. Each of these technologies also has associated costs (e.g. capital costs, O&M costs, discount rates). In most instances, these costs are input in the form of curves, i.e. as elasticities and as such, they are described as demand curves in that they can meet varying levels of energy demand at varying levels of cost (Loulou et al., 2005).

There are 73 technologies available in the transport sector, including 17 car technologies (see Table B.1), 20 bus technologies, 12 road freight truck technologies and 10 train technologies. Fuels options include diesel, gasoline, ethanol, electricity, LPG, natural gas, compressed hydrogen etc.

Table B.1: Private car technologies and associated investment costs

Technology	Description	Investment Cost - 2010 (k€/vehicle)	Investment Cost - 2050 (k€/vehicle)
TCARSDL101	Bio-diesel Car	9.8	10.7
TCARSDME110	DME Car	11.5	10.5
TCARSDST101	Diesel Car	8.5	8.5
TCARSDST210	Hybrid Diesel Car	13.4	12.4
TCARSEL110	Electric Car	20.7	10.0
TCARSETH101	Ethanol Car	9.0	9.9
TCARSFTD110	FT-Diesel Car	9.7	10.7
TCARSGAS101	CNG Car	9.8	10.7
TCARSGH2110	Internal Combustion Hydrogen Car (Compressed)	13.5	12.5
TCARSGH2210	Fuel Cell Hydrogen Car (Compressed)	14.0	13.0
TCARSGSL101	Gasoline Car	8.6	9.5
TCARSGSL201	Hybrid Gasoline Car	16.5	11.2
TCARSLH2110	Internal Combustion Hydrogen Car (Liquefied)	13.5	12.5
TCARSLPG101	LPG Car	9.6	10.5
TCARSMtaH101	IC Methanol Car	9.0	9.9
TCARSMtaH210	Fuel Cell Methanol Car	14.0	13.0
TCar_PIH	Plug-in Hybrid Car	17.0	13.0

Each technology has an associated investment cost as well as operational and maintenance costs. Fuel costs are also accounted for but these are endogenous to the model and are not classed as inputs. The technology costs can be arranged in order of increasing cost to give a cost curve of various technology options which can help identify which technologies may be chosen before others in the TIMES model. A sample of such a cost curve for select technologies (in this case a subset of the private car technologies) is given in Figure B.1 below. Other inputs for each technology include fuel type and efficiency.

The outputs from the transport sector include the list of selected technology options in each time period; the associated cost of investment in this suite of technologies; the resulting fuel costs, which

are calculated endogenously within the model and are an output rather than inputs. The results can distinguish between different fuels used, including the level of electrification, the possible adoption of a number of different types of biofuel and whether these are imported or produced domestically. The model outputs the CO₂ emissions and can distinguish between direct and indirect emissions. TIMES can also model NOX and SOX emissions.

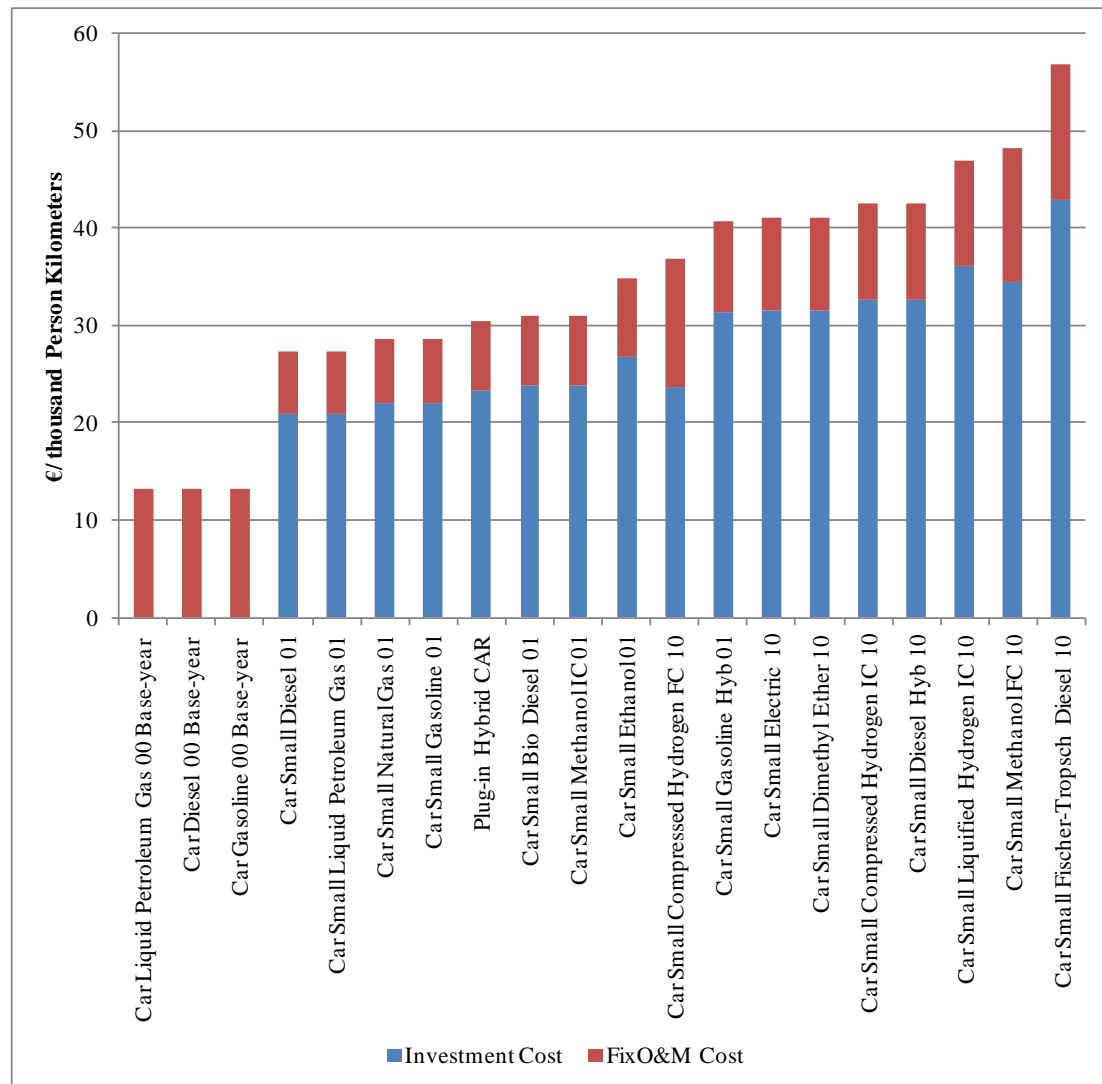


Figure B.1: Comparison of private car investment and O&M costs

Drivers

Key data driving the Irish TIMES model are the macro-economic projections of GDP, GNP, private income, population and number of households that is generated using the Economic and Social Research Institute (ESRI) long-term macro-economic model. These parameters are used to generate energy service demand parameters, which are the key quantities that the Irish TIMES model must produce an energy system to satisfy. In total, there are 60 different types of energy services for the

transport, residential, agricultural, commercial, industry and non-energy sectors. Some examples include residential space heating (peta-joules, PJ), commercial refrigeration (PJ), industry iron & steel (millions of tonnes, Mt), transport car distance (millions of passenger kilometres, Mpkkm) and transport road freight (millions of tonne kilometres, Mtkm). For each modelling period out to 2050, energy service demand parameters are input and the Irish TIMES model must serve these parameters at least cost.

Each energy service demand is projected forward from the base year 2010 to 2050 using exogenously specified demand driver rates and demand elasticities. Demand driver rates (DDR) and demand elasticities constitute the energy service demand driver (ESD Driver) over the period using the following formulas:

$$DDR(t) = \left(\left(\frac{DemandDriver(t)}{DemandDriver(t-1)} \right) - 1 \right) \quad (B.1)$$

$$ESDdriver(t) = (1 + DDR(t) * elasticity(t))^{periodlength} * (1 - AEEI) \quad (B.2)$$

The elasticities were calculated for the period to 2020 by comparing the reference energy scenario within Irish TIMES against Ireland's published national energy forecasts. Table B.2 gives the demand driver for each energy service demand and Table B.3 provides 5-year projection incremental percentage increases for each of these drivers. Private car transport is driven by gross national product (GNP) with projections taken from the ESRI Medium term review 2013, recovery scenario.

Table B.2: Transport energy service demands and demand drivers

Description	Drivers
Car - Long Distance Travel	GNP per Capita
Car - Short Distance Travel	
Motorcycles	GNP
Intercity Bus	Population
Urban Bus	
Passenger Rail - Light	
Passenger Rail - Heavy	
Rail Freight	Transport and Communications GVA
Road Freight	
International Aviation	
Domestic Aviation	
Navigation	
Navigation Bunker	

Table B.3: Transport related driver projections

Driver	2010 - 2015	2015 - 2020	2020 - 2025	2025 - 2030	2030 - 2035	2035 - 2040	2040 - 2045	2045 - 2050
GNP	7%	19%	12%	12%	6%	6%	6%	6%
Population	2%	4%	4%	3%	2%	2%	2%	2%
GNP per Capita	5%	14%	8%	9%	4%	4%	4%	4%
Gross Value Added to Transport and Communications	18%	24%	7%	9%	6%	6%	6%	6%

Resource Potential and Fuels

The resource potential applies mostly to commodities and supply curves, i.e. what is the cost of each commodity at various levels of supply. The resource potential also applies to technologies, particular renewable energy technologies and their resource. There is a limit to the amount of onshore wind power that can be constructed in Ireland based off research from Chiodi (2010), DCENR (2008) and SEI (2004), and is summarised in Table B.4. The ocean energy resource potential is aligned with the ocean energy roadmap (SEAI, 2010) and set at 29 GW in 2050. The maximum capacity for hydro energy has been set at 224 MW for large plants and at 250 MW for run of river plants. The existing 292 MW pumped hydro storage plant is also modelled. The use of geothermal energy in Ireland is limited only to small installations in the residential and services sector mostly for space and water heating purposes. Because solar and geothermal energy contribute marginally to scenarios outputs, no maximum potentials have been provided in the model.

Table B.4: Onshore and offshore wind capacities

Technology	Unit	2006	2010	2015	2020	2025	2030	2050
Onshore Wind	GW	0.3	2.1	3.1	5.3	5.6	5.9	6.9
Offshore Wind	GW	0	0.1	0.6	1	7.7	3.8	7.5

The commodity supply curves and renewable resource for Irish TIMES have been carefully scrutinized and updated based on most recently available data, local knowledge or known technical limits (Ó Gallachóir et al., 2012).

Projections for future fuel prices for key fuel commodities (e.g. coal, oil and gas) are taken from IEA world energy outlook (Figure B.2) (IEA, 2012b).

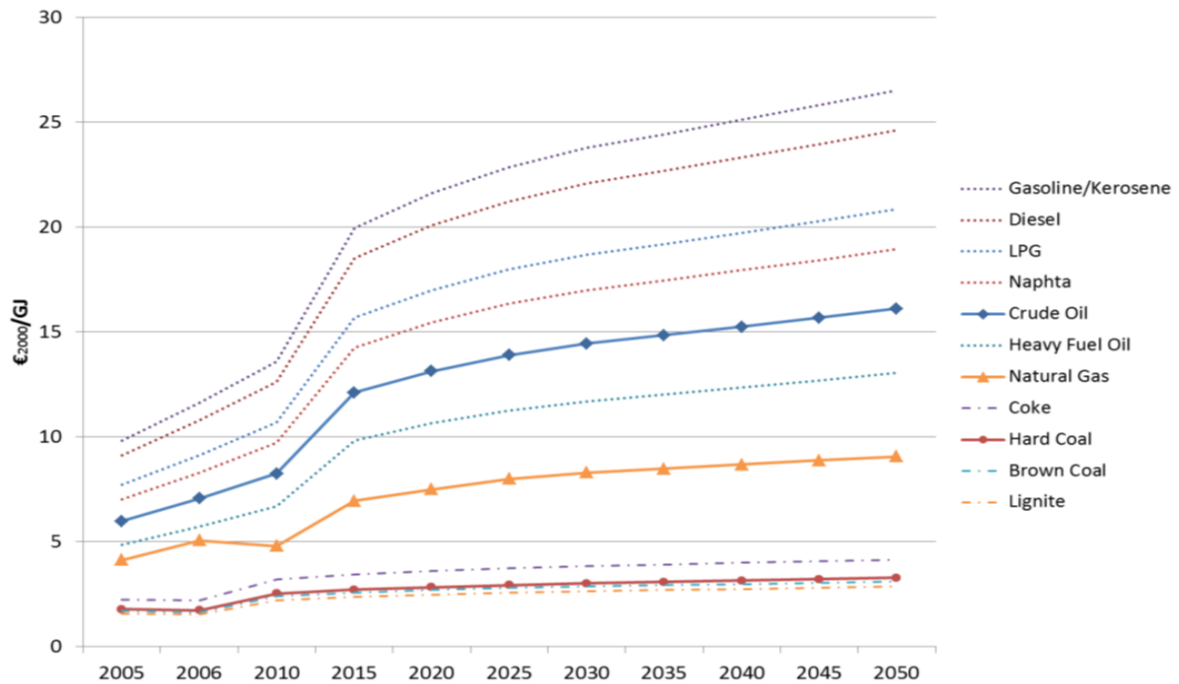


Figure B.2: Fuel price projections

Given the importance of renewable energy for the achievement of mitigation targets, Ireland's energy potentials and costs are based on the most recently available data. The total resource capacity limit for domestic bio-energy has been set at 1,230 ktoe for the year 2020 and at 3,022 ktoe by 2050, based on the estimates listed below (see Table B.5).

Table B.5: Biofuel energy potential

Commodity Unit	Unit	2005	2010	2020	2030	2040	2050
Agricultural waste ¹	ktoe	25.0	153.1	188.0	188.0	188.0	188.0
Starch crop ¹	ktoe	0.0	31.6	47.4	79.0	79.0	79.0
Grassy crop (Miscanthus) ¹	ktoe	2.7	4.0	28.0	211.3	394.7	910.3
Woody crop (Willow) ¹	ktoe	13.1	19.7	137.6	284.4	431.2	722.0
Forestry residues ¹	ktoe	62.3	93.5	109.1	109.1	109.1	109.1
Biogas ^{1,2}	ktoe	30.8	38.4	284.9	382.6	480.3	578.0
Municipal waste ¹	ktoe	71.1	142.2	155.5	155.5	155.5	155.5
Rape seed ²	ktoe	1.7	7.2	14.3	14.3	14.3	14.3
Industrial waste ¹	ktoe	0.0	2.3	7.0	7.0	7.0	7.0
Wood processing residues ¹	ktoe	258.9	258.9	258.9	258.9	258.9	258.9

¹(Smyth et al., 2010) ²(BSG, 2004)

The cost assumptions for domestic bio-energy commodities are based on McEniry et al. (2011) for biogas from grass, Kent et al. (2011) for forestry, Clancy et al. (2008) for willow and miscanthus crops and Clancy et al. (2012) for wheat crops. Cost estimates on bio-energy imports are based on an SEAI report by Clancy et al. (2012) (see Table B.6). Cost assumptions for bulk renewable energy technologies were recently updated based on studies by DECC (Brinckerhoff, 2011) (for wind energy) and Brinckerhoff (2012) (for solar). Electricity prices are calculated endogenously in the model.

Table B.6: Biofuel energy costs

Commodity Costs (€2000/GJ)	2005	2010	2020	2030	2040	2050
Agricultural waste	4.10	4.60	5.20	5.20	5.20	5.20
Starch crop	8.16	7.73	7.06	6.59	6.59	6.59
Sugar crop	7.57	7.39	7.15	7.03	7.03	7.03
Grassy crop	4.48	4.30	4.20	4.20	4.20	4.20
Woody crop	2.57	2.41	2.21	2.10	2.10	2.10
Forestry residues	2.74	2.63	2.53	2.53	2.53	2.53
Biogas (from grass)	4.50	4.10	3.70	3.70	3.70	3.70
Municipal waste	0.80	0.40	0.20	0.20	0.20	0.20
Rape seed	2.74	2.67	2.54	2.43	2.43	2.43
Industrial waste	0.01	0.01	0.01	0.01	0.01	0.01
Wood processing residues	3.25	3.35	3.45	3.45	3.45	3.45

Discount Rates

The model uses a general discount rate (year dependent), as well as technology specific discount rates (period dependent). The former is used to: a) discount fixed and variable operating costs, and b) discount investment cost payments from the point of time when the investment actually occurs to the base year chosen for the computation of the present value of the total system cost. The latter are used only to calculate the annual payments resulting from a lump-sum investment in some year. Thus, the only place where the technology specific discount rate intervenes is to compute the Capital Recovery Factors.

Each individual investment physically occurring in year k , results in a stream of annual payments spread over several years in the future. The stream starts in year k and covers years $k, k+1, \dots, k+ELIFE-1$, where ELIFE is the economic life of the technology. Each yearly payment is equal to a fraction CRF of the investment cost (CRF = Capital Recovery Factor). Note that if the technology

discount rate is equal to the general discount rate, then the stream of ELIFE yearly payments is equivalent to a single payment of the whole investment cost located at year k , in as much as both have the same discounted present value. If however the technology's discount rate is chosen different from the general one, then the stream of payments has a different present value than the lump sum at year k . It is the user's responsibility to choose technology dependent discount rates, and therefore to decide to alter the effective value of investment costs.

In the Irish TIMES economic values are specified in constant Euros of the year 2000. Costs – of building a process, maintenance, or importing a commodity – in year y are given in constant euros of year y , without inflation. Economic values of different years are discounted to the base year 2000 with a general social time preference or real term discount rate. In the Irish TIMES a 6% real term discount rate is assumed, but lower or higher values can be used in sensitivity runs. The technology specific discount rates used in the Irish TIMES for private cars is taken as 17.5%.

Appendix C: Market Share Algorithm

In Chapter 4, heterogeneity is modelled exogenously in the Irish TIMES and CarSTOCK models separately to provide a somewhat more realistic market share change based off cost and consumer preference. This method is employed in Irish TIMES by placing a user constraint on the private car sector to represent heterogeneity amongst consumer choice – as the model is based on least cost, a sudden penetration of a cheaper technology void of this added constraint would create a sudden and unrealistic shift in the market share towards this option. This study represents the market uptake of new technologies using the CIMS market share algorithm (see Equation C.1). CIMS is a hybrid energy-economy model developed at Simon Fraser University that simulates capital stock turnover through time as technologies are acquired, retired, and replaced (Jaccard, 2009) This equation uses capital costs (CC), maintenance costs (MC), energy costs (EC), intangible costs (i) and a discount rate (r) to calculate the market share of a technology j in year n when competing against K technologies.

$$MS_j = \frac{\left(CC_j * \frac{r}{1 + (1 + r)^{-n}} + MC_j + EC_j + i_j \right)^{-v}}{\sum_{k=1}^K \left(CC_k * \frac{r}{1 + (1 + r)^{-n}} + MC_k + EC_k + i_k \right)^{-v}} \quad (C.1)$$

This market share algorithm is useful in capturing the effect of the intangible costs associated with alternative fuelled vehicles, such as consumer hesitation towards purchasing new technologies and range anxiety. This intangible cost is calibrated off current market shares in 2013 and 2015, extrapolated to 2050. Capital costs were taken from the current average market prices of vehicles by engine band weighted against the vehicle stock as it stands today. A decrease in the capital cost of pure electric vehicles (PEV) and plug in hybrids (PiH) of 53% over the next 6 years is based on a learning curve assumed from IEA (2016e). The fuel costs are taken based off 2015 market prices and projected forward using fuel costs from IEA (2016d), the discount rate is chosen at 24% and heterogeneity, v, is assumed as 15 based on Kamiya (2015). This list of parameters is summarised in Table C.1. The resulting market shares are entered as a capacity limit for market uptake of private car technologies as a user constraint in Irish TIMES.

Table C.1: Irish TIMES baseline market share algorithm parameters

Technology	2015				2050			
	CC	MC	EC	i	CC	MC	EC	i
Petrol Car	€28,316	€5,598	1.26 c/ltr	-	€28,316	€5,598	1.66 c/ltr	-
Diesel Car	€28,316	€5,598	1.19 c/ltr	-	€28,316	€5,598	1.57 c/ltr	-
BEV	€21,490 ¹	€5,505	0.13 c/kWh	€29,241	€10,041 ¹	€5,505	0.13 c/kWh	€3,843
PHEV	€31,450 ²	€5,455	0.81 c/ltr	€10,542	€14,695 ²	€5,455	1.05 c/ltr	-

¹ Price includes government grant of €5,000 towards Pure Electric Vehicle purchasing

² Price includes government grant of €2,500 towards Plug in Hybrid Electric Vehicle purchasing

Similarly, the penetration of alternative fuelled private cars is simulated in the CarSTOCK model through a bounded market share sale to a greater extent, with limitations placed on the maximum penetration over time based on Equation C.1 above. The modelling framework of the CarSTOCK model allows for a greater description of vehicle technologies relative to the TIMES model. Three engine sizes divide petrol and diesel fuelled cars in the model into the engine size classes small (<1300 cc), medium (1301 – 1900 cc) and large (>1900 cc). Capital costs, operation and maintenance costs, and fuel costs are based off current market prices for all technologies as above, while intangible costs are chosen to account for consumer preference for each technology and are calibrated also using current market shares. Smaller sized vehicles are generally cheaper than their larger sized counterparts, yet larger vehicles tend to have a higher market share, relating to a higher intangible cost due to consumer preference for small vehicles, and a lower intangible cost for larger vehicles (see Table C.2).

Table C.2: CarSTOCK baseline market share algorithm parameters - 2015

	CC	MC	EC	i
BEV	€21,490 ¹	€5,202	0.13 c/kwh	€23,955
PHEV	€31,450 ²	€5,252	0.81 c/ltr	€15,799
Petrol - Small	€14,949	€5,261	1.26 c/ltr	€17,362
Petrol - Medium	€20,829	€5,796	1.26 c/ltr	€14,796
Petrol - Large	€43,502	€6,666	1.26 c/ltr	€10,008
Diesel - Small	€14,995	€5,261	1.19 c/ltr	€25,987
Diesel - Medium	€24,180	€5,796	1.19 c/ltr	€9,770
Diesel - Large	€43,705	€6,666	1.19 c/ltr	€78

¹ Price includes government grant of €5,000 towards Pure Electric Vehicle purchasing

² Price includes government grant of €2,500 towards Plug in Hybrid Electric Vehicle purchasing